MASTER'S DISSERTATION

# Happiness, Debt & Depression

*Is there a relationship between debt and depression in South Africa?*


**Nathan Sklair (SKLNAT002)**

Dissertation supervisor: Professor Justine Burns

Master of Commerce in Applied Economics

School of Economics

University of Cape Town

This page is intentionally left blank.

Acknowledgements: I would like to thank my supervisor, Professor Justine Burns, for her inspiration, guidance and invaluable advice, not only over the duration of this dissertation but since the beginning of my career in economics. I am grateful for the continued support from my family, friends and colleagues. I look forward to continuing the quest to find meaningful insights on happiness in the future.

CONTENTS

## 1. Introduction

South African consumers are consistently among the most indebted people in the world (World Bank, 2018). The credit-active[1] population is 48.8%, while the reported ratio of household debt to income is 71.9% (SARB, 2018), and 39.1% of the population have an impaired credit record (National Credit Bureau, 2018). Given that the South African population already faces high levels of inequality, high levels of consumer indebtedness could exacerbate this inequality by increasing the divergence between those who pay and those who earn interest (World Bank, 2018).

Mean depression scores in South Africa are also significantly higher than in other countries (Ardington & Case, 2010), and approximately 33% of South Africans are expected to suffer from at least one form of mental illness (Lund, 2012). The South African Depression and Anxiety Group (SADAG) reports that 20% of South Africans experience depression at least once in their lifetime (SADAG, 2017). Furthermore, South Africans are unlikely to receive professional help for mental health conditions as practitioners in the field are not distributed equally across the country's medical services centres (Lund, Kleintjes, Kakuma & Flisher 2010).

The World Happiness Report (2018) ranked South Africa 105th out of 156 countries on the World Happiness Index. According to media reports, many South Africans who report feeling stress or anxiety, report doing so largely due to their debt burden (Khumalo, 2017). It is therefore clear that there is a growing need to understand the relationship between debt and depression more deeply.

Recent literature on the economics of happiness suggests that the relationship between debt and depression may not be coincidental (Gathergood, 2012). The literature posits a positive, diminishing relationship between income and happiness (Frey, 2008). In Western economies, happiness rises with Gross Domestic Product (GDP), until a GDP threshold is reached, after which happiness levels remain constant or experience small decreases (Easterlin, 2001). However, in non-Western, developing economies, happiness levels continue to rise modestly, indicating that a

[1] Credit-active means the individuals has at least one form of debt.

happiness threshold from rising GDP may not have yet been reached (Clark, Frijters, & Shields, 2008).

Traditional economic models such as Dynamic Consumption Theory assert that, by increasing consumption, increases in income lead to increases in utility (Deaton, 2005). However, as many consumers finance their consumption through debt (Choonoo, 2016), what is not well understood – and what is largely ignored by such models – is the relationship between debt and happiness[2].

There are a number of possible relationships between happiness and debt that can be posited. Indeed, on the one hand, acquiring debt may lead to a change in the mental health status of an individual. For example, this effect may be positive, through an increase in utility directly from the consumed items, or negative, owing to increased stress as a result of taking on debt. On the other hand, an alternative causal pathway is possible: mental health may affect an individual's consumption behaviour, through a decrease in self-control, resulting in a preference for present consumption over future consumption (Ifcher & Zarghamee, 2011 : Achtziger, Hubert, Kenning, Raab, & Reisch, 2015). If an individual values present consumption over future consumption, there may well be a risk of increased indebtedness. Indeed, the limited research in this area points to a need for further exploration and evidence of (I) the causal direction between mental health and debt, and (II) whether the relationship is positive, negative, or non-existent.

In light of this, the current paper aims to examine this relationship between debt and mental health[3]. The paper adds to the literature on the relationship between debt and depression in three ways. Firstly, it investigates the possibility of causal relationship between debt and depression by exploiting the panel presented in the NIDS dataset. This is a significant contribution as many studies also make only investigate cross-sectional data, which limits the ability to which one can establish the direction of causality between mental health and socio-economic and demographic characteristics (Lund et al., 2013). Secondly, as there are multiple forms of debt (mortgage,

[2] Happiness measures are typically assumed to proxy for underlying latent 'utility'.
[3] Mental health, happiness and depression are often used interchangeably, although specific terms are used when appropriate.

student, formal, and informal), each with a unique experiential quality, this paper examines each form of debt and its relationship to depression. Finally, this paper investigates the relationship between debt and mental health in a developing economy – as most of the existing literature available on debt and mental health only investigates this relationship in western, developed economies.

In order to examine the causal relationship between debt and depression, this study uses 5 waves of panel data from the National Dynamic Income Study (NIDS) from 2008 to 2017. By applying a logistic fixed effects model, the panel nature of the dataset is exploited. The econometric analysis controls for within person-specific effects, unobserved heterogeneity, and omitted variable bias, as per the methodology employed in Keese & Schmitz (2014).

The rest of this paper is structured as follows. Section 2 provides an overview of the inter-temporal economic model, forming the basic framework for this paper, as individuals may acquire debt considering consumption for the present and future. Section 3 discusses the literature regarding happiness and utility, as new developments in data collection allow us to proxy for happiness through self-reported measurements of utility. Section 4 discusses how debt is thought about in relation to individual utility, and an individual's lifetime utility optimisation. Section 5 reviews the existing literature on debt and depression. Section 6 includes a brief discussion on debt and depression in South Africa. Section 7 includes an overview of the data and measurement used in this paper for the analysis. Section 8 provides the descriptive statistics of the sample considered including their demographic characteristics, and the prevalence of debt and depression across these demographic characteristics. Section 9 provides an overview of the empirical strategy, discussion the measures of control, as well as a discussion on the use of odds ratios in this analysis for the logistic regression estimates. Section 10 provides a detailed overview of the estimated results. Section 11 is a discussion on the results and the main findings, comparing my finding to existing literature. Section 12 includes a brief discussion on some of the robustness checks conducted, as well as the limitations of this study.

Finally, the paper concludes that (I) Individuals who acquire informal debt have an increase in the odds of being showing depressive symptoms in both the current and future period. On the other hand, individuals who exhibit evidence of depressive symptoms in the current period have an increase in the odds of acquiring debt in the current period – but past period depressive symptoms do not appear to predict future period informal debt. Therefore, informal debt appears to exhibit a characteristics of a bi-directional causal relationship in the current period, with informal debt associated with long term depressive symptoms. (II) Individuals with secure or mortgage debt exhibit a decrease in the odds of being depressed in the future, and (III) there is evidence that acquiring formal debt and being depressed decreases the odds by which an individual exhibits symptoms of depression in the future. This means that for unproductive debt categories debt appears to exhibit a negative effect on mental health and thus a decrease in lifetime utility. However, for productive debt categories such as secure debt, there is a positive effect on future mental health which may be argued to be an improvement in lifetime utility.

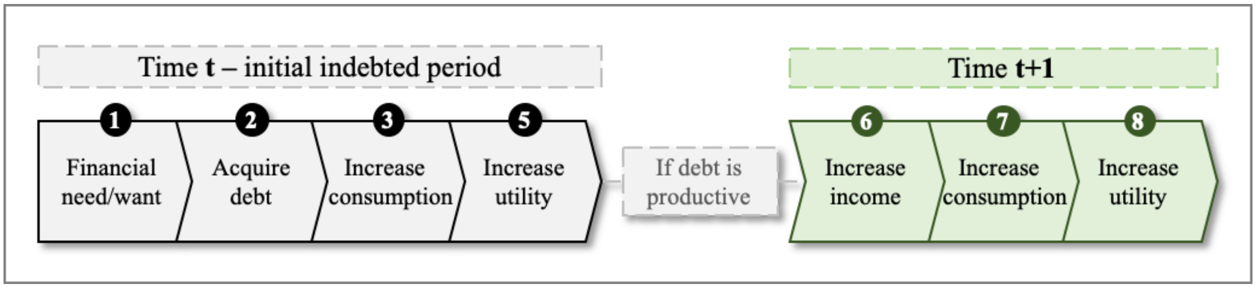
## 2. The consumer debt journey

While it has been established that there is a positive link between income and subjective well-being, the role of debt in an individual's financial portfolio, and the mechanism through which debt affects subjective well-being is not well understood (Gathergood, 2012). Indeed, income and happiness may move together up to a point (Easterlin, 2001). Yet, if one relies on debt finance to supplement income shortfalls, this could undermine increases in utility through rises in debt stress. To understand this in more detail, I use the Life Cycle Hypothesis as a point of departure, after which I consider the role of debt stress in affecting net happiness (Deaton, 2005). For many economists, questions regarding utility optimisation are a vital concern. Traditionally, economists have operationalised the measurement of utility by using income as a proxy. One such model which illustrates this is Franco Modigliani's Life Cycle Hypothesis, the description of which follows below (Ando & Modigliani, 1963):

*"…utility is assumed to be a function of his aggregate consumption in current and future periods. The individual is then assumed to maximise his utility subject to the resources available to him, his resources being the sum of current and discounted future earnings over his lifetime and his current net worth."* (Ando & Modigliani, 1963)

The Life Cycle Hypothesis describes a process whereby an increase in income results in an increase in consumption, improving the individual's lifetime utility. In traditional Dynamic Consumption Theory models, such as Modigliani's life cycle hypothesis, debt is used as a consumption smoothing instrument, aimed at optimising individual lifetime utility. The high-level intertemporal journey of debt for an individual is illustrated in Figure 1, below.

**Figure 1. The debt process in Dynamic Consumption Theory**




In this model, in the face of an income shortfall, individuals acquire debt in order to finance short term consumption. This allows the individual to increase their marginal utility in the short term at time *t*. If the debt acquired at time *t* is productive, meaning that the individual can at least pay off the debt in *t*+1, then the individual may experience an increase in their propensity to consume, and therefore their utility. For example, the described productive debt could take the form of student debt to increase future salaries, or through a mortgage loan to increase net assets in the future. Productive debt may take many forms; but it must be able to increase one's lifetime consumption, compared to having not taken out the debt. If acquiring debt is not productive, and individuals become over-indebted, the long-term effects can result in a decrease in income and thus a decrease in lifetime utility through lower future consumption.

## 3. Happiness as a measure of utility

Of course, viewing a decrease in utility through the lens of a decrease in consumption is only one possible understanding. The literature regarding the economics of happiness critiques the assumption that income and net worth are the only determinants of utility, as income alone does not provide a complete picture of the utility equation (Frey, 2008).

In light of recent developments that allow for self-reported measurements of individual well-being, proponents of the economics of happiness argue that subjective measures of happiness ought to be factored into the utility equation (Frey, 2008). Metrics on happiness in the academic literature are mostly captured as measures of subjective well-being, such as life satisfaction or mental health. Measurement of such subjective well-being such as life satisfaction is typically captured as a one-shot question. For example, Posel & Casale (2011) report on subjective well-being in South Africa based on answers to the question, "Using a scale of 1-10 where one means ‘very dissatisfied' and ten means ‘very-satisfied' how do you feel about your life as a whole right now?".

Measurements of mental health in surveys tend to use multiple questions on the mental status of the individual to construct an overall score for mental health. Two of the most commonly used measures are the General Health Questionnaire (GHQ) (Clark, 2003), the Center for Epidemiologic Studies Depression Scale (CES-D) (Radloff, 1977). The GHQ consists of 12 questions asking individuals to self-report how frequently they experience depression, anxiety, and other stress-related symptoms. The answers to these questions are then consolidated into a “caseness” score, from which the mental health status of the individual can be determined. The score provides a measure of depressive or negative mental health symptoms. The CES-D follows a similar method by asking individuals some questions on how frequently they experience negative emotions such as anxiety, as well as positive emotions such as happiness or hope (Radloff, 1977). The questions are then consolidated to create a score. From these scores, a cut-off score is then created to indicate mild to significant depression.

These measures of utility and happiness separate from income demonstrate some possible ways of further developing the analysis of utility beyond a mere factor of income, such as by including mental health experiences and subjective happiness estimates.

Adding further factors into the utility analysis helps to explain the imperfect correlation between income and happiness. In the income-happiness related literature, a statistically significant positive correlation exists between income levels and happiness. In the USA, for example, the correlation between income and happiness is 0.2 (Easterlin, 2001). Additionally, data from the Euro-Barometer survey found that individuals in the top income quartile were "fairly satisfied" or "very satisfied" with life 88% of the time – 22 percentage points higher than individuals in the lowest income quartile (Tella, MacCulloch, & Oswald, 2003). However, at the macroeconomic level, a phenomenon known as the Easterlin Paradox occurs (Easterlin, 2001). The Easterlin Paradox is the trend that while some countries experience significant increases in real GDP per capita, average happiness seems to remain constant or exhibit small decreases (Clark et al., 2008). Some economists conclude that the positive correlation between income and happiness is owing to an initial increase in income; but above a certain level, the marginal happiness from additional income tends to zero (SACHS, 2016).[4]

It may be, as Kahneman (1999) describes, that personal finances are only one domain of happiness. In developed economies, such as the USA, it is argued that the Easterlin Paradox is observed because satisfaction from the income domain has become satiated at the macroeconomic level (Sachs, Layard, & Helliwell, 2018). Developing economies, on the other hand, appear to exhibit moderate increases in happiness with rising income and may still reap the happiness benefits from increased income, especially when considering the high levels of poverty and inequality (Clark et al., 2008). In other words, they have not yet reached the turning point after which happiness no longer rises with income. As many individuals in developing economies have significant financial constraints, acquiring debt may act as a buffer in allowing individuals to meet their required level of consumption, in the absence of income.

There is an ongoing debate regarding whether GDP per capita should be the ultimate indicator of national success. One of the arguments against such an approach is that GDP does not consider the effects on income inequality (Clark et al., 2008). This debate has led economists to suggest happiness as the ultimate national objective (Sachs, 2016). Consequently, some countries have begun redefining their success metrics to align with the subjective well-being of their population (Sachs et al., 2018). In 2018, the New Zealand government announced that the 2019 budget would report on the effect of national spending on the population's happiness. The New

[4] Importantly, most of the evidence exhibiting the characteristics of the Easterlin Paradox exists in research conducted in developed economies.

Zealand government have published that they intend to create "a more rounded measure of success, as a country and as a Government" (New Zealand Government, 2018). Similarly, in 2017, the leadership of Dubai begun working on a happiness index within the Smart Happiness Project Evaluation Tool (SHAPE). The goal of SHAPE is to measure the happiness of cities per funds spent by local management (World Economic Forum, 2018).

At the individual level, the relationship between happiness and income is bi-directional causal. On the one hand, happier individuals exude a more positive attitude and therefore tend to be more successful in their careers, thus resulting in increased income (Frey, 2008). On the other hand, as per Dynamic Consumption Theory, individuals who receive more income may be happier owing to their increased propensity to consume. While this represents a fairly sophisticated understanding of the relationship between income and happiness, the role and effect of debt in the consumer's financial portfolio and its relations to happiness remains unclear.

As mental health is a subject of increasing interest among academics, a number of papers have investigate the possible determinants of mental health and depression (Lund, 2012). Given South Africa's history of racial and wealth inequality, some core research has focused on race, and other household characteristics, such as household size, as key determinants of depression (Eyal, 2016).

## 4. Debt and happiness

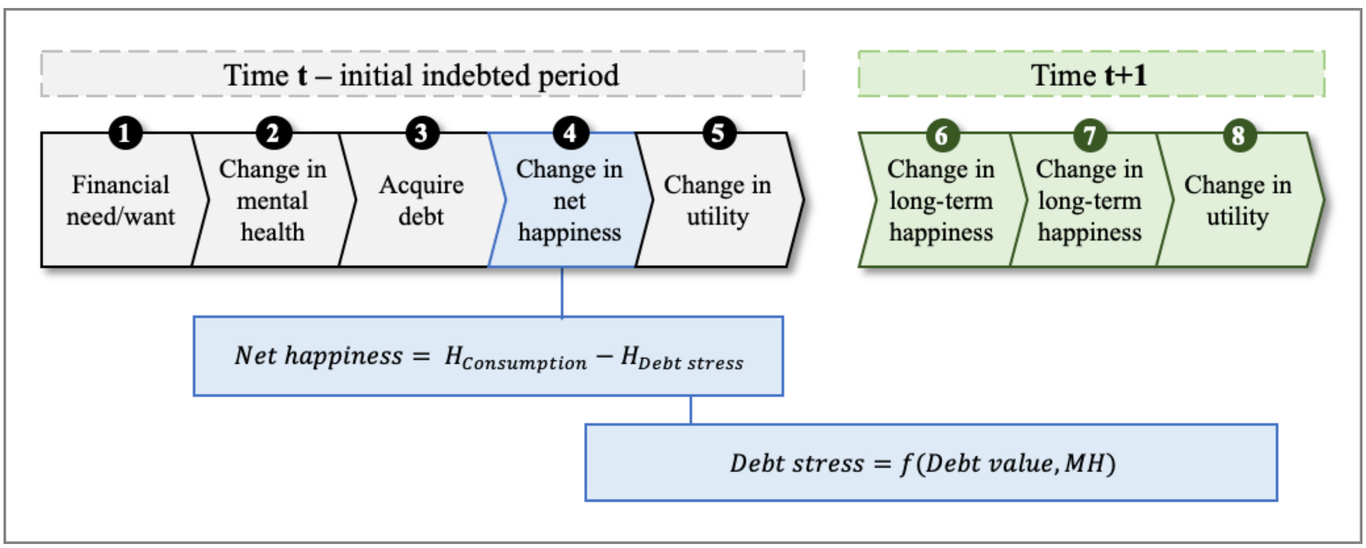
There are two primary reasons why happiness is of interest when considering the consequences of debt and, more broadly, financial decision making. The first reason is, as discussed, a growing interest by some economists in approximating individual utility by using self-reported measures of well-being or happiness, rather than as a direct function of lifetime income (Frey, 2008). If debt plays a role in affecting individual mental health by, for example, increasing depression, then bringing happiness into the utility optimisation problem could result in shifts in public sector policies, or private sector strategies by changing or supplementing the key success metric.

The second reason is that one's happiness may affect one's propensity to become indebted (Achtziger et al., 2015). Given that South Africans are among the most indebted in the world, if a change in one's mental health, or a pre-existing mental health condition, increases the propensity for consumers to become indebted, mental health can, among other reasons, be an essential focus for policymakers in order to target the levels of South African indebtedness.

The theoretical model on the relationship between debt and mental health adds mental health to the individual intertemporal debt journey. This addition adds two primary elements to this journey. First, it includes the possible effect of one's mental health on their consumption behaviours. Second, by measuring mental health, we can observe net happiness (utility) from debt-based consumption. Net happiness, in this model, is the happiness derived from consumption,

subtracted by the possible debt stress associated with taking on debt. The intertemporal debt journey including mental health is illustrated in Figure 2, below.

**Figure 2. Including happiness in the intertemporal debt journey**




As illustrated above, the main addition to the model is the inclusion of the possible negative utility derived from debt stress. Debt stress is a function of debt value, income, and mental health. The debt value and income levels are combined to provide a debt-to-income ratio, and a zero value for debt means that no debt stress exists. Importantly, the model includes mental health (MH) as part of the debt stress function. As discussed by Bridges & Disney (2010), this is because an individual's pre-existing mental health status may contribute toward their perception of the seriousness of their debt problem.

Therefore, three relationships emerge. The first is that mental health may play a role in the propensity to acquire debt, through present bias. The second is that debt may affect mental health through debt stress, and the third is that pre-existing mental health issues may exacerbate the perception of the individual's debt problem.

## 5. What we currently know about debt and happiness

Much of the existing research that discusses debt and mental health acknowledges that there is insufficient literature investigating the causal relationship between debt and mental health, although there is some broader literature on the association between debt and mental health (Tay, Batz, Parrigon, & Kuykendall, 2017).

This section provides a more detailed breakdown of the existing literature on the relationship between subjective well-being and debt[5]. At a high level, there are four forms, or categories, of debt which appear most frequently in the literature on debt (Tay et al., 2016). These are: (1) formal debt (2) informal debt, (3) student debt, and (4) mortgage or secured debt.

Formal debt consists of any loan from a formal lending institution. This includes sub-categories such as vehicle finance, credit cards, store credit, and others. Formal debt typically entails less risk on behalf of the lending institution, so the recipients are more likely to be financially stable through the means of consistent employment, a secure salary or assets or minimum level of education – although the exact requirements that formal lending institutions hold for their customers vary slightly by country.

[5]. It may be the case that the relationship between debt and mental health has more to do with net wealth. This relationship was noted by Headey & Wooden (2004). However, a full investigation should be the subject of future research.

Informal debt, in the existing literature, includes title loans[6], pawn loans, cash advances, and rapid tax refunds, among other categories (Sweet, Kuzawa, & McDade, 2018). Informal debt, if not acquired from friend, family or employers, are ordinarily short-term loans with high-interest rates, and often target individuals who have limited resources for their more immediate financial needs (Bertrand & Morse, 2011). These individuals are typically poor, older, geographically remote, or vulnerable in some way that they are unable to access formal credit markets (Sweet et al., 2018). Therefore, the key differences between formal debt and informal debt are the set of requirements lenders set out for potential debtors, and the socio-economic positions of the debtors that are consequently attracted by each.

Student debt is used to finance present studies and may present a significant financial burden to new graduates (Tay et al., 2017). In theory, student debt is incurred with the objective of increasing one's future income through additional levels of education, thus increasing lifetime utility. Finally, Mortgage or secure debt is debt acquired by an individual to finance a property, often their own, to reduce the opportunity cost of renting accommodation. Secure debt is typically taken out for longer periods of time, at lower interest rates and is similar to formal debt in those institutions who provide secure debt require their customers to be financially stable through the means of a consistent salary or have sufficient assets.

Each of the four forms of debt discussed above have different experiential qualities and meet different financial needs (Sweet et al., 2018). Because of this, the relationship between debt and mental health for each of these forms of debt ought to be considered in their own right. Therefore, the discussion continues by exploring the literature on the associations and possible causal links between each form of debt and mental health.

The literature on the determinants of different forms of debt in South Africa includes factors such as income, age, level of education, marital status, household size, self-perceived physical health status, geographical area type, and dwelling type (Choonoo, 2016). More broadly,

[6] Loans based on the legal ownership of vehicle as collateral in order for an individual to acquire debt

research in the determinants of wealth in South Africa investigates similar determinants as those in the debt literature – as debt is a subset of wealth (Daniels & Augustine, 2016).

Table 1 summarises the existing literature on formal, informal, and student debt. Beginning with formal debt, there is a statistically significant relationship between formal debt and depression. Formal debt is generally associated with higher levels of depressive symptoms. Only two of the papers provide us with a quantifiable measure of the relationship. The results in relation to formal debt are relatively consistent, showing an increase in depression by ~9%, as found in both the Berger, et al. (2016) and Brown et al. (2005) papers. According to Berger, et al. (2016) the increase in depressive symptoms, measured as 12 CES-D questions, is exhibited when comparing both formal debt at an indicator level, as well as in debt value.

As has been noted, there is a limited quantity of literature on debt and mental health. The scarcity of literature is even greater when it comes to informal forms of debt. The current research by Sweet et al. (2018), investigates informal debt including by asking individuals if they had ever had a short-term loan of any kind, including payday loans, title loans, cash advances, or any other form of short-term loan, excluding borrowing money from family or friends. Sweet et al. (2018) only find a significant association between payday loans and feelings of anxiety, but no statistical relationship with other mental health elements such as anger or depression. The psychological characteristics found in Sweet et al. (2018) are measured through a 20-item CES-D scale.

**Table 1: Research on formal debt, informal debt and student debt**

### Research on formal debt

| Author | Main Finding | **Association or Causation** (And method used if causation) |
|---|---|---|
| Berger et al., 2016 | • Having debt was associated with having ~9 % more depressive symptoms<br>• 10 % increase in debt value was roughly associated with ~14 % increase in depressive symptoms<br>• Having short-term debt associated with ~8 % more depressive symptoms | Panel survey with fixed effects regression<br>Association found |
| Brown, Taylor, & Price, 2005 | • A 10% increase in the level of outstanding credit reduces the probability that a household reporting a maximum GHQ12 score by 0.092 – poorer mental health | Association |
| Drentea & Reynolds, 2015 | • There is a statistically significant relationship between indebtedness and symptoms of depression, anxiety, and anger | Association |

### Research on informal debt

| Author | Main Finding | **Association or Causation** (And method used if causation) |
|---|---|---|
| Sweet et al., 2018 | • Individuals with a history of short-term loans ~15% more likely to report feeling anxious | Association |

### Research on student debt

| Author | Main Finding | Association or Causation (And method used if causation) |
|---|---|---|
| Walsemann, Gee, & Gentile, 2015 | • Cumulative accumulation in student loans significantly associated with poorer psychological functioning<br>• Students from families with negative net worth exhibit improved psychological functioning with increased values of student loans | Association |
| Tay et al., 2017 | • Loans have a statistically significant association with financial worry, and financial worry, a statistically significant association with life satisfaction | Association |

With regards to student debt, Tay et al. (2017) report that individuals with student loans are more likely to be financially stressed, and therefore more stressed in general. The study by Dwyer et al. (2011), not reported in Table 1, found that in a restricted sample of youth aged 18 to 34 with access to credit, those who obtain formal credit are more likely to report positive effects of mastery and self-esteem, although these self-esteem effects diminish with age. In contrast to the other literature, this paper suggests that debt may have positive effects on individual mental health.

It is clear that each particular form of debt may tend to have different effects on happiness or utility. With regards to stress, high debt-to-income ratios, over-indebtedness, and problem debt have been used to describe the more unfavourable characteristics of personal debt. In the literature, debt is also commonly discussed concerning over-indebtedness. In (Keese & Schmitz, 2014), over-indebtedness refers to the situation whereby net income after debt repayments is below the social assistance level – the level below which the government provides individuals with a basic level income. While this relates to net wealth or debt-to-income ratios, many papers include a binary variable for over-indebtedness for any category of debt (Drentea & Reynolds, 2015).

A more extreme version of the debt-to-income ratio is the characterisation of problem debt. Gathergood (2012) discusses that an individual has problem debt when any of the following three criteria are met: (1) difficulty meeting one's mortgage repayments, (2) being at least two months late on one's mortgage repayments, or (3) reporting that meeting one's consumer credit repayments places a heavy burden on one's household (Gathergood, 2012).

While the acquisition of debt can often be a signal of some degree of financial difficulty, the forms of secure or mortgage debts – given the stringent requirements to obtain them – are collateralised forms of debt which signal a certain level of initial capital and stability. Table 2 summarises the relationship between household debt and depression. Secure debt is often seen as a long-term investment such as taking out a mortgage for a house which, the eventual ownership of which may have significant lifetime welfare-improving characteristics. Most of the literature investigating the causal relationship between debt and mental health is housed within these studies on secure or mortgage debt.

The Bridges & Disney (2010) result alludes to the existence of reverse causality in that individuals with poorer mental health may be more likely to become indebted, and that there are endogeneity concerns when looking at debt as the trigger for a change in mental health. The Gathergood (2012) study uses local variations in housing prices as a source of exogenous variation – an instrumental variable approach. Gathergood (2012) finds that individuals with "problem debt", in areas where housing prices are decreasing, report higher GHQ scores (higher GHQ scores indicating poorer mental health). Keese & Schmitz (2012) exploit their panel and find that their fixed effects model exhibits a positive relationship between the debt-to-income ratio and poorer psychological health, as measured by the GHQ score.

**Table 2: Research on Secure/mortgage debt**

| Author | Main Finding | **Association or Causation** (And method used if causation) |
|---|---|---|
| Gathergood, 2012 | • Individuals in arrears, with a £10,000 fall in house price, experience an increase in their GHQ score of 0.64 points - worse mental health | Causation<br><br>**IV:** Exogenous variation in local-level housing prices |
| Currie & Tekin, 2015 | • Foreclosure leads 0.783 more hospital visits. No statistically significant relationship to mental health | Causation<br><br>**IV:** Foreclosure |
| Keese & Schmitz, 2012 | • FE only: an increase in consumer credit and housing repayments by ten percentage points of income imply an increase in GHQ score of 0.1607 and 0.2287, respectively. Statistically significant result<br>• FE only: statistically significance that being over-indebted results in a 0.673 increase in GHQ score<br>• FE + lagged debt variables: only mortgage debt is significant, and the effect size is a 0.149 increase in GHQ for a 10-percentage point increase in the value of debt repayments | Causation<br><br>**Causal control:** Using fixed effects and a lagged debt variable in a panel study |
| Bridges & Disney, 2010 | • No significant evidence of direct effects of increased indebtedness on psychological well-being | Causation<br><br>**Causal control:** Exploit panel for financial difficulties but not subjective well-being |
| Brown, Taylor, & Price, 2005 | • Household heads with mortgage loans do not have significant differences in their GHQ scores | Association |
| Cairney & Boyle, 2004 | • Individuals with mortgages have lower levels of stress than renters | Association |

To summarise, the existing literature on debt and mental health predominantly reports an adverse effect of debt and mental health but provides little or insufficient evidence for a conclusive finding on the effect of mental health on debt, or debt on mental health. As there is a lack of consistency of measurement within the existing literature, with much of the causal literature reporting on "problem debt", rather than debt in general, it appears that the only consistent story that the existing literature tells us is that "problem debt" increases depressive symptoms.

Importantly, most of these studies consider "problem debt", being debt which individuals already experience difficulty paying. For example, in Gathergood (2012), problem debt is reported as having missed 2 or more mortgage payments. Currie & Tekin (2015), on the other hand, only look at mortgage debt in terms of foreclosure. Keese & Schmits (2014) provide evidence that an inability to pay off one's mortgage debt could be more stressful than debt associated with formal credit, as it may cause one to lose one's property. Much of the existing literature on the causal relationship between debt and happiness echoes this idea that an inability to pay mortgage debt, or experiencing foreclosure, results in poor psychological health (Gathergood, 2012, Currie & Tekkin, 2015).

In the literature discussing the causal relationship between mental health and debt, most of the statistical significance in the relationship is lost. Some of the papers attribute this to the possible two-way causal relationship. Bridges & Disney (2010) find that after controlling for person-specific factors, there is no evidence that increased indebtedness affects psychological well-being. However, Bridges & Disney (2010) report that there is a weak effect of worsening health on the perception of subjective financial well-being, where subjective financial well-being is an indicator for whether an individual is financially stressed. Individuals with mortgage debt, on the other hand, are less likely to report feeling stress than those who rent their property.

Furthermore, as the existing literature is limited to studies and datasets exclusively conducted in developed, Western economies, there is a gap in the understanding of the relationship between debt and mental health in the developing world. Therefore, the analysis of debt and depression in a non-Western, developing economy is a key contribution of this paper.

## 6. The South African Debt Landscape

Despite, being ranked as one of the most indebted nations in the world, this section starts with two positive facts on debt in South Africa. Firstly, the percentage of South Africans with an impaired credit record has been declining, and now sits at 39.1% of the population. Secondly, the South African Reserve bank reported a decline in household debt, as a percentage of disposable income, from 85.7% in 2008 to 71.9% in 2017 (SARB, 2018). During this time, the dominant contribution of outstanding debt has shifted from mortgage debt to consumer credit.

However, it is still the case that South African consumers are heavily indebted, with the South African population reporting one of the highest prevalence of indebted consumers in the (World Bank, 2018). Indeed, over 80% of the South Africa population is reported to be in debt (World Bank, 2018). Table 3 draws on information from the Department of Trade and Industry, providing an overview of those in debt. Of South African debtors, the prevalence of debt across various debt forms, as well as the proportion of the value of debt is reported. Secured credit appears to be the most common form of debt, at 34.17%, followed by mortgage debt at 30.45%. Unsecured debt is the third most common form of debt. More detail on the distribution of debt is provided in the discussion on NIDS.

**Table 3: Distribution of debt among indebted South Africans as of Q4 2017**

| Debt Agreement | Proportion of total debt value | Proportion of cases |
|---|---|---|
| Mortgage | 51.50% | 30.45% |
| Secured Credit | 23.16% | 34.17% |
| Credit facility | 12.94% | 12.90% |
| Unsecured | 9.67% | 18.47% |
| Short term | 0.15% | 2.75% |
| Developmental | 2.58% | 1.26% |

Source: Department of trade and industry (National Credit Regulator, 2018)
Note: In the table above, secured credit is separated from mortgages. This is because of slightly different definitions based on the source. In the National Credit Regulator data mortgages are separated from other forms of secured (asset backed credit). Secured credit in this table is analogous to formal debt as described in my analysis based on NIDS.

In South Africa, there has been an increasing concern that debt is leading to higher levels of depression (SADAG, 2017). Importantly, articles published in the media state that financial stress is a significant contributor to depression (Business Report, 2018). This report is consistent with the existing literature which suggests that adverse financial circumstances tend to lead to an increase in the likelihood of depression.

However, based on the media reports, it is unclear which individuals suffer depression owing to debt. On one reading, it appears as if those who report financial stress often report having debt as a cause of this stress – meaning that it is a subset of the financially stressed individuals. The lack of clarity may result in adverse conclusions regarding the effects of debt on individuals. These conclusions may then be used to drive policy, business initiatives, or be used as a reference for individuals in their social lives. Returning to the earlier discussion on income and happiness, evidence stating that an increase in income can increase happiness until a particular point, above this point additional levels of income have no significant positive effect on happiness. This evidence is discussed in the context of a developing economy.

Evidence from the Grameen Bank of Bangladesh, microfinance in a developing context, made credit more secure and more accessible for more impoverished individuals (Yunus, 2007). The Grameen bank reported evidence that its implementation caused an increase in income, decreasing poverty levels. If this applies to the South African context then we may observe positive outcomes from debt.

## 7. Data, measurement and descriptive statistics

The data used in this paper comes from five waves of the National Income Dynamic Study (NIDS), a nationally representative face-to-face longitudinal survey of South African individuals and households repeated every two years. The years associated with each wave in this paper are

2008, 2010, 2012, 2014 and 2017 (Southern Africa Labour and Development Research Unit, 2018). The survey captures a wide range of socio-economic data, providing a consistent measurement of the dimensions of well-being in South Africa over time (Southern Africa Labour and Development Research Unit, 2018). Within the NIDS questionnaire a wide variety of asset-related data including the composition of individual and household income, asset ownership, as well as individuals' debt portfolios. The survey is also incredibly useful to understand the well-being of the population as it asks a number of mental health-related questions regarding happiness, subjective well-being, and depressed. Therefore, the NIDS data is incredibly useful for this study as it captures a significant amount of information regarding both debt and mental health.

The debt data consists of indicators for the type of debt, the monthly payments on the debt, as well as the total outstanding value of debt – although there is a significant degree of unanswered questions regarding the debt values, as discussed in section 12 in this paper. The questions on mental health include a one-shot measure of subjective well-being, a one-shot question asking respondents to compare their happiness level in the current period compared to 10 years ago, and ten CES-D questions regarding individual mental health. In this paper, I use only the indicators for the components of debt, and the CES-D measures, to minimise issues that arise from missing data.

### a. Measurement of mental health

The primary measurement of mental health in my analysis takes the form of an indicator variable for whether an individual shows evidence of depressive symptoms or not. The CES-D indicator is constructed from a series of individual CES-D questions within the NIDS. The CES-D measurement, initially developed by Radloff (1977) consists of ten questions regarding the mental well-being of respondents – creating a variable called CES-D 10. As the measure includes of multiple items, and aim at capturing a comprehensive view mental health analogous to a psychiatric diagnosis, the CES-D score provides a sophisticated measure of mental health, compared to some one-shot questions.

The CES-D questions ask respondents to rank, on a Likert scale from 1 to 4, how frequently in the past seven days the respondent has experienced any of the following symptoms:

1. I was bothered by things that usually don't bother me
2. I had trouble keeping my mind on what I was doing
3. I felt depressed
4. I felt that everything I did was an effort
5. I felt hopeful about the future 6. I felt fearful
7. My sleep was restless
8. I was happy
9. I felt lonely
10. I could not "get going"

The Likert scale is structured as follows: (1) none of the time (less than one day), (2) some or a little of the time (one to two days), (3) occasionally or a moderate amount of the time (three to four days), to (4) all of the time (five to seven days).

Following the approach taken by Eyal (2016), and validated by Myer et al. (2008), the 10 questions are converted into a mental health index, based on a score out of 30, that makes working with the data easier to work with and interpret. This approach involves rescaling each of the 10 questions from 0 to 3 and summed to create a score out of 30, this allows for 0 values to exist in the metrics and provides meaning to the sum of adding all the variables[7]. Note that for the positively phrased questions regarding happiness and hope, the scale is reversed in the data so that the happiest is closest or equal to 0 – consistent with the other 8 questions for which better mental health is associated with a lower response value. Following the score out of 30, a cut of score above 10 is used to signal moderate to intense levels of depression[8], as is consistent with the existing literature. For the remainder of this paper, referring to individuals as depressed in the NIDS data set (having a CES-D score above 10), must be taken to mean showing evidence of depressive symptoms – and not clinical depression.

[7] If we were to add them in their current form, the score would be one out of 40, but the minimum value would be 10. This would make working with and interpreting the data more difficult – unnecessarily so. We have to acknowledge that the initial scaling is more likely to facilitate easier data capture – rather than ease of analysis.
[8] Intense levels of depression when referring to NIDS, or depressed later on, can be interpreted as showing evidence of depressive symptoms.

In terms of validity of the CES-D 10 measure, and the cut off of 10, the measure and score have been validated for five key components. These components include:

1. Use as an initial screening tool for mental health in South Africa (Pretorius, 1991).
2. Internal consistency within South Africa (Hamad et al., 2008).
3. External consistency in countries outside of South Africa (Myer et al., 2008).
4. Consistency with other diagnostic tools and tests such as the Rockliff Depression Rating scale, the Hamilton, the Edinburgh, amongst other tests (Das et al., 2007).
5. Sensitivity to the cut off of ten. That is, studies that use other cut offs for depression, such as a score of 15, yield similar results to a cut off of 10 to indicate depression (Kilburn et al., 2015).

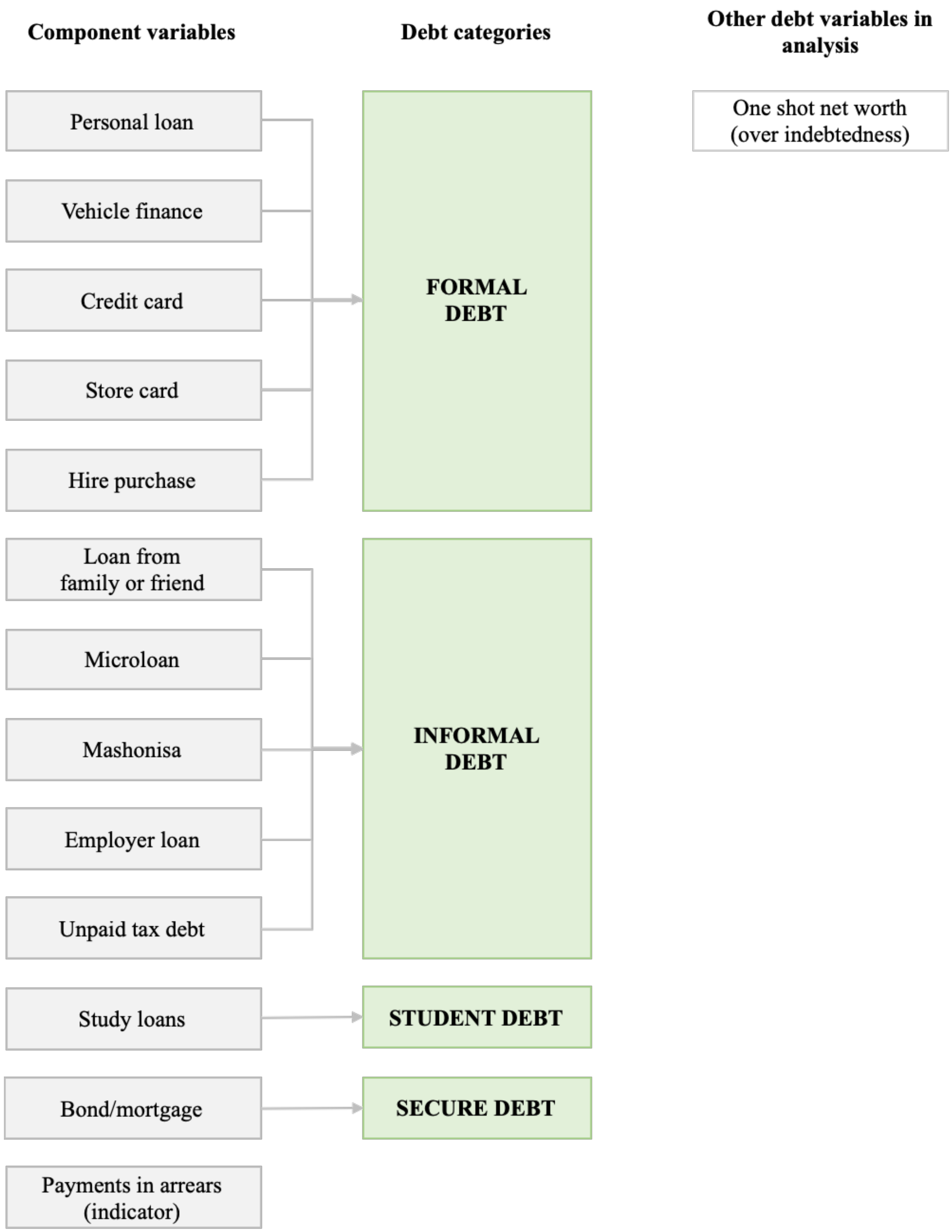
**b. Measurement of debt**

The construction of the debt data used in the analysis is illustrated in Figure 3. For the debt data used in this paper, I use only the indicator level data regarding each type of debt, as well as a one-shot question regarding net worth. The indicator level data consists of multiple questions regarding an individual's debt status for each particular type of debt. I consider each of these types of debt as "components" or sub-categories.

These components are then bundled together to create broader debt indicators category or form of debt as discussed earlier in the literature. These categories are formal debt, informal debt, student debt, and secure debt. As illustrated in Figure 3, formal debt and informal debt consist of 5 components each, while student debt and secure debt are captured by one particular component indicator and do not consist of multiple sub-categories. The debt components were placed into debt categories, requiring an individual only to have answered one component to place more broadly into any of the categories.

The question on one-shot net worth, which could signal over-indebtedness, but is not an accurate measure of over-indebtedness is also included in the analysis predominantly as a measure of control for over-indebtedness in the absence of a better quality variable. Data on whether an individual has payments in arrears does not form part of the data analysis as this is a characteristic of debt and not a debt category in and of itself.

*Figure 3. Construction of debt categories from debt components in NIDS*



While the indicator variables have a low non-response rate between waves 1 and 5 for the NIDS, the debt data is not collected consistently across waves. For example, questions on employer loans, outstanding tax and debt in arrears is not collected in waves 1 and 3. While data on the monthly payments and balance for debt for each component of debt the response rates on the value of debt are also incredibly low and not captured consistently throughout the survey, and therefore the monthly debt values (in absolute terms)are not investigated in my analysis.

The grouping of debt into formal debt, informal debt, student debt, and secure debt helps address possible adverse outcomes from the missing data in variables such as employer loans and outstanding tax for certain years. This is because each of the variables (employer loans and outstanding tax) are included in the informal debt category. Because informal debt is a dichotomous variable which is true when an individual has at least one of the sub-categories of debt, the effect of missing data for certain years on the sample size, because of its effect on the broader categories (formal, informal etc.), is minimised.

### c. Control variables in the analysis

To adjust for some of the possible confounding factors, and as per good econometric practice, I include several socio-demographic and demographic controls. These include age, age squared (in the regression) level of education, marital status as a binary for whether an individual is a couple or not, household size, self-perceived physical health status, geographical area type, and dwelling type. In addition to this, individual employment income is used. The income variables in the descriptive statistics are split into categories based on previous research on income and depression as measured with the CES-D score (Baron, Davies, & Lund, 2017).

## 8. Descriptive statistics and empirical strategy

The sample for this study consists of employed individuals of working age (between 15 and 65) from 2008 to 2017. Given the possible bi-directional causal relation, individuals who had at least one observation missing over the five waves were excluded from the data owing to concerns regarding attrition between waves. Thus the data used in this paper consists of a strongly balanced panel which should limit the noise of the sample introduced by individual heterogeneity, although individuals with severe depression may fall out of the sample (Eyal, 2016). The attrition that may be present is addressed by using sample weights, where possible, in the analysis. However, according to Eyal (2016) this attrition is only marginally different from those who do not exhibit symptoms of poor mental health. The total number of people-years in the sample is 26 434 consisting of 10 905 individuals observed over 5 years.

Following the precedent in previous literature, only the employed individuals of the working age population are included in the sample (Keese & Schmitz, 2014). Keeping only the working-age (ages 15-65), the employed population reduces problems of reverse causality as a result of individuals entering and exiting employment. This is because unemployment has been previously linked to reporting problem debt, as well as poor mental health. Therefore if individuals move between employment throughout waves, a degree of control over the sample is lost. Therefore, my approach attempts to simplify the sample as much as possible, while also allowing me to compare my results more closely with existing literature that established causality for non-mortgage debt. Furthermore, credit markets are much more difficult to access without a source of income, as is evident by Table A1 in the Appendix, illustrating that employed individuals are more likely to have debt compared to unemployed individuals. A limitation of only including employed individuals of working age in my sample is that any estimates may be underestimated in areas where individuals are using the non-labour market income to secure debt.

Table 4 summarises the critical mean demographic characteristics e sample used in my analysis and compares individuals with any form of debt, to individuals without debt. To test the significance of these differences, I conducted a t-test for years 2014 and 2017 as a robustness check to facilitate the discussion on the critical characteristics in the sample. At the outset, the mean prevalence of depression is 18%, while individuals who have debt appear to be less likely to be show evidence of depressive symptoms, and have a lower mean CES-D 10 score than individuals without debt.

There is a significant difference in the average income between indebted and non-indebted individuals, having a mean salary from employment of R7 873.74 and R3 577.70 respectively. Debtors appear to have a higher mean level of education of 10.81, compared to 8.63 for individuals without any debt. Furthermore, 73% of those with debt live in urban areas, compared to those without debt, of which only 54% live in urban areas. Therefore, the picture illustrated by Table 4 is that many of the debt characteristics appear to be related to the ease of financial access through means of higher income, education, and living in urban areas. It is also evident that the prevalence of depression is somewhat consistent with reports from the South African Depression and Anxiety Group reports that 20% of South Africans will report feeling depressed at least once in their lifetime.

From Table 4 we can see that indebted individuals exhibit lower scores for mental health and are less likely to show evidence of depressive symptoms. To build on this, Table 5 provides a view of the prevalence of depression by year and compares those in debt to those without debt. Although depression scores in wave 1 are higher in general, the difference in the prevalence of depression between those in debt and those without debt appears to show small decreases. The prevalence of depression between those in debt and those not in debt is nine percentage points in 2008, seven percentage points in 2010, and decreases slowly, reaching a minimum difference of 1 percentage point in 2014, and the difference increasing again to 4 percentage points in 2017. In general, it appears that there is a diminishing difference in depression between those in debt and those not in debt.

**Table 4. Descriptive statistics of mean characteristics for people-years from 2008-2017**

| Variables | Mean | Has any debt | No debt | Significance in 2014 | Significance in 2017 |
|---|---|---|---|---|---|
| Depressed (CESD-10 >10) | 0.18 | 0.15 | 0.20 | ** | ** |
| CES-D 10 | 6.65 | 6.23 | 6.96 | *** | *** |
| Age | 38.12 | 38.83 | 38.48 | *** | * |
| Female | 0.49 | 0.52 | 0.50 | *** | |
| Married or living together | 0.43 | 0.48 | 0.39 | *** | *** |
| Years of education | 9.65 | 10.81 | 8.63 | *** | *** |
| Bad physical health | 0.02 | 0.02 | 0.03 | | |
| Total income | R5 692.85 | R7 873.64 | R3 577.70 | *** | *** |
| Household size | 4.40 | 4.12 | 4.53 | *** | * |
| African | 0.75 | 0.72 | 0.78 | *** | |
| Coloured | 0.18 | 0.18 | 0.18 | *** | *** |
| Asian | 0.02 | 0.02 | 0.01 | | |
| White | 0.06 | 0.08 | 0.03 | *** | *** |
| Urban | 0.62 | 0.73 | 0.54 | *** | *** |
| Negative net worth | 0.05 | 0.08 | 0.02 | *** | *** |
| ***Overall N*** | **24 902** | **10 628** | **14 274** | | |

Source: NIDS 2008-2017, own calculations
Notes: Data from all waves of strongly balanced panel of only employed individuals of working age (15-65). Data is only weighted for the significance tests using post stratified weights.
Tests of significance are show differences between those who have debt and those who do not have debt in each of the years 2014 and 2017, for those waves only. This is because these are the only waves for which significance tests could be done with all the relevant data. This is not comparing all of waves 1 to 5 to each of the years described above.
*** p<0.01, ** p<0.05, * p<0.1

**<u>Table 5: Prevalence of depression by year</u>**

| Year | All | Std. | Has Debt | Std | No Debt | Std | Sig |
|---|---|---|---|---|---|---|---|
| 2008 | 0.21 | 0.01 | 0.16 | 0.01 | 0.25 | 0.01 | *** |
| 2010 | 0.15 | 0.01 | 0.11 | 0.01 | 0.18 | 0.01 | *** |
| 2012 | 0.17 | 0.01 | 0.16 | 0.01 | 0.18 | 0.01 | *** |
| 2014 | 0.18 | 0.01 | 0.18 | 0.01 | 0.19 | 0.01 | |
| 2017 | 0.18 | 0.01 | 0.16 | 0.01 | 0.20 | 0.01 | ** |

Source: NIDS 2008-2017, own calculations
Notes: Data from all waves of strongly balanced panel of only employed individuals of working age(15-65)
Data is weighted using the post stratified weight in each wave
Significance *** p<0.01, ** p<0.05, * p<0.1

Thus far Table 4 has provided an idea who in the sample is likely to be indebted, and Table 5 a view comparing the prevalence of depression over time based on debt status. The next point of interest is to understand the state of mental health, across the sample, for individuals with and without debt. Table 6 provides the prevalence of depression for our sample, by demographic characteristics, assisting with building the story regarding how debt and depression may be related at a sample level.

The differences in the prevalence of depression across age groups appear relatively constant over time, with those in debt consistently exhibiting a lower prevalence of depression. Males seem to exhibit intense symptoms of depression with a lower probability than women, while both genders are less like to be depressed when having debt. The values on the level of education are interesting. Specifically looking at individuals with no education, individuals with debt have a depression prevalence of 21%, while individuals without debt have a depression prevalence of 27%, this gap appears to decrease as education levels rise.

**Table 6. Prevalence of depression levels by demographic characteristics and debtor status**

| | All | Has Debt | No Debt |
|---|---|---|---|
| **Age** | | | |
| 15-17 | 0.15 | - | 0.15 |
| 18-24 | 0.18 | 0.15 | 0.18 |
| 25-34 | 0.17 | 0.14 | 0.18 |
| 35-44 | 0.18 | 0.16 | 0.20 |
| 45-54 | 0.20 | 0.17 | 0.22 |
| 55-65 | 0.20 | 0.15 | 0.23 |
| **Gender** | | | |
| Male | 0.16 | 0.14 | 0.18 |
| Female | 0.20 | 0.17 | 0.22 |
| **Couple status** | | | |
| Single(widow, divorce, never married) | 0.20 | 0.18 | 0.22 |
| Married or living with partner | 0.15 | 0.13 | 0.18 |
| **Education** | | | |
| No Schooling | 0.26 | 0.21 | 0.27 |
| Primary | 0.23 | 0.21 | 0.23 |
| Highschool no matric | 0.19 | 0.18 | 0.19 |
| Matric | 0.15 | 0.13 | 0.17 |
| Further Education | 0.16 | 0.16 | 0.16 |
| Higher Education | 0.12 | 0.11 | 0.14 |
| **Income from employment** | | | |
| R1-R500 | 0.23 | 0.22 | 0.23 |
| R501-R1000 | 0.23 | 0.21 | 0.23 |
| R1001-R2000 | 0.22 | 0.20 | 0.22 |
| R2001-R5000 | 0.17 | 0.17 | 0.17 |
| R5001-R10 000 | 0.13 | 0.13 | 0.14 |
| R10 001-R15 000 | 0.12 | 0.11 | 0.12 |
| 15 001-R20000 | 0.11 | 0.09 | 0.18 |
| R20001+ | 0.11 | 0.10 | 0.13 |
| **Physical health** | | | |
| Fair physical health | 0.18 | 0.15 | 0.19 |
| Bad physical health | 0.41 | 0.37 | 0.44 |
| **Race** | | | |
| African | 0.20 | 0.18 | 0.22 |
| Coloured | 0.13 | 0.11 | 0.14 |
| Asian/Indian | 0.13 | 0.11 | 0.16 |
| White | 0.09 | 0.08 | 0.12 |
| **Geographical area** | | | |
| Rural | 0.20 | 0.16 | 0.22 |

| | | | |
|---|---|---|---|
| Urban | 0.17 | 0.15 | 0.19 |
| **Net worth** | | | |
| Non-negative | 0.16 | 0.14 | 0.17 |
| Negative | 0.18 | 0.18 | 0.20 |
| **Full Sample** | 0.18 | 0.15 | 0.20 |
| ***N*** | 24 589 | 10 517 | 14 068 |

Source: NIDS 2008-2017, own calculations
Notes: Data from all waves of strongly balanced panel of only employed individuals of working age(15-65)
For characteristics with less than 5 or no observations, where no value between 0 and 1 was given, the values are marked as blank.
Data is not weighted

In general, Table 6 shows that respondents with debt appear to have a lower likelihood of reporting symptoms of intense depression. However, so far the sample has been split into those with or without debt in the broader sense. If different forms of debt have different experiential qualities, then the tables above may be heavily influenced by some types of debt, or if various forms of debt have different effects on mental health or vice versa, then we won't be able to understand this dynamic fully. Therefore, to better understand the relationship between debt and mental health, the discussion proceeds by splitting the sample into the different forms of debt. The following tables consider various kinds of debt, and how the sample is distributed between each of these different forms of debt.

First, Table 7 provides a view of the prevalence of each component of debt over time across the sample. Table 7 is then complemented by Table 8 which displays the prevalence of each component of debt over the five waves for credit-active individuals. That is individuals who have at least one type of debt. Table 8 includes how the prevalence of debt has changed over time for the consolidated debt categories (formal, informal, student, and secure).

It can be seen from Table 7 and Table 8 that data for employer loans, tax debt, and debt in arrears are not collected for wave 1 and wave 3. To address this missing data, the variables are placed as a subset of the broader debt categories (in this case there are informal debt). Placing these variables as part of informal debt reduces the degree to which missing data affects the analysis. Table 8 shows the components of each combined debt category from wave 1 to wave 5. It is observed that the majority of formal debt can be attributed to store cards. Furthermore, it can be seen that only a small portion of the report having informal debt. This could be because of possible under reporting of informal debt in the chosen sample, perhaps owing to sensitivities around debt in general. In order to understand if this is the case, I check the data in my robustness check, in Section 12 of this paper.

**Table 7: Prevalence of debt amongst the employed population**

| **Debt component** | 2008 | 2010 | 2012 | 2014 | 2017 |
|---|---|---|---|---|---|
| Personal loan | 10% | 9% | 13% | 17% | 19% |
| Vehicle finance | 9% | 6% | 5% | 7% | 7% |
| Credit card | 14% | 11% | 12% | 11% | 9% |
| Store card | 23% | 19% | 24% | 31% | 31% |
| Hire purchase | 5% | 4% | 4% | 6% | 4% |
| Microloan | 1% | 1% | 1% | 1% | 1% |
| Mashonisa | 1% | 1% | 1% | 2% | 2% |
| Famliy or friend | 2% | 2% | 2% | 6% | 4% |
| Employer | | 1% | | 1% | 1% |
| Outstanding tax | | 0% | | 0% | 0% |
| Debt in arrears | | 2% | | 2% | 1% |
| Study loan | 1% | 1% | 1% | 1% | 1% |
| Bond | 11% | 11% | 9% | 7% | 5% |
| **Total credit active** | **42%** | **40%** | **45%** | **55%** | **52%** |

Source: NIDS 2008-2017, own calculations
Notes: Data from all waves of strongly balanced panel of only employed individuals of working age(15-65)
Data is weighted using the post stratified weight in each wave

**Table 8: Prevalence of debt by wave for individuals with at least one form of credit**

| Debt component | 2008 | 2010 | 2012 | 2014 | 2017 |
|---|---|---|---|---|---|
| Personal loan | 23% | 22% | 29% | 32% | 37% |
| Vehicle finance | 22% | 16% | 12% | 14% | 14% |
| Credit card | 33% | 27% | 26% | 20% | 17% |
| Store card | 55% | 46% | 54% | 56% | 59% |
| Hire purchase | 11% | 9% | 10% | 10% | 7% |
| Microloan | 2% | 3% | 1% | 2% | 2% |
| Mashonisa | 3% | 3% | 3% | 3% | 4% |
| Famliy or friend | 5% | 5% | 4% | 11% | 7% |
| Employer | | 2% | | 1% | 2% |
| Outstanding tax | | 0% | | 1% | 1% |
| Debt in arrears | | 4% | | 4% | 1% |
| Study loan | 3% | 2% | 2% | 2% | 2% |
| Bond | 26% | 27% | 20% | 14% | 9% |
| **Debt category (combined)** | | | | | |
| Formal debt | 89% | 82% | 88% | 87% | 89% |
| Informal debt | 10% | 13% | 7% | 16% | 15% |
| Secure debt | 3% | 2% | 2% | 2% | 2% |
| Student debt | 26% | 27% | 20% | 14% | 9% |

Source: NIDS 2008-2017, own calculations
Notes: Data from all waves of strongly balanced panel of only employed individuals of working age(15-65)
Data is weighted using the post stratified weight in each wave

Table 9 presents the prevalence of depression for each category and sub-category of debt. Looking at the data in Table 9, the prevalence of depression for individuals with informal debt is 23% on average, comparing this to formal debt which presents a mean prevalence of depression of 15%, while student debt and mortgage debt have a prevalence of 14% and 11% respectively. Furthermore, the component of debt associated with the highest depression is from mashonisas, followed by outstanding debt from one's employer. In general, only the informal debt categories are associated with higher prevalence of depression compared to not having debt. In other words, the mean prevalence on having formal debt, student debt, and secure debt independently exhibit that the mean prevalence of depression is lower when individuals have each of these categories of debt, compared to not having debt typically acquired through formal lending markets.

**Table 9: Prevalence of depression by debt type for individuals with and without debt**

| | Debt | No debt |
|---|---|---|
| **Formal debt (any)** | 0.15 | 0.20 |
| Personal loan | 0.16 | 0.18 |
| Vehicle finance | 0.10 | 0.19 |
| Credit card | 0.12 | 0.19 |
| Store card | 0.15 | 0.19 |
| Hire purchase | 0.14 | 0.18 |
| **Informal debt (any)** | 0.23 | 0.18 |
| Microloan | 0.18 | 0.18 |
| Mashonisa | 0.29 | 0.18 |
| Family or friend | 0.23 | 0.18 |
| Employer | 0.24 | 0.17 |
| Outstanding Tax | 0.22 | 0.17 |
| Has debt in arrears | 0.19 | 0.17 |
| **Student debt** | 0.14 | 0.18 |
| **Secure/mortgage debt** | 0.11 | 0.19 |

Source: NIDS 2008-2017, own calculations
Notes: Data from all waves of strongly balanced panel of only employed individuals of working age(15-65)
Data is not weighted

Table 9 illustrates that debt acquired on the informal credit market exhibits the highest prevalence of depression. I break up the sample into the mean descriptive characteristics based on each debt category. The mean descriptive based on each debt category is presented in Table 10. From this data, we can see that individuals with informal debt, as per the above table, have a mean prevalence of depression which is much higher compared to the characteristics of individuals with debt that is not informally acquired. Individuals with informal debt also appear to have a lower salary (R4 864.47) compared to individuals in other debt categories.

Interestingly, and somewhat surprising is that the mean age of the sample with student debt is 44, which is older than the average for the rest of the categories. One of the reasons for this could be that I excluded all the unemployed individuals from the sample., especially if many of the students are considered unemployed and are younger. Individuals with secure debt have smaller households, compared to individuals with other forms of debt. It is apparent that a significantly higher proportion of Africans have informal debt, compared to other race groups.

Finally, and interestingly, the prevalence of negative net worth is higher for individuals with secure/mortgage debt, at least ten percentage points higher than the other groups. This may be because individuals do not yet own their homes and therefore have a significant outstanding debt balance.

**Table 10: Mean characteristics of the population by debt category**

| | **All** | **Formal debt** | **Informal debt** | **Secure debt** | **Student debt** |
|---|---|---|---|---|---|
| Depressed | 0.18 | 0.15 | 0.23 | 0.14 | 0.11 |
| CESD-10 | 6.65 | 6.14 | 7.51 | 5.97 | 5.21 |
| Age | 38.12 | 38.67 | 39.08 | 36.80 | 44.00 |
| Female | 0.49 | 0.53 | 0.47 | 0.57 | 0.43 |
| Years of education | 9.65 | 11.03 | 9.21 | 12.47 | 12.43 |
| Bad physical health | 0.02 | 0.02 | 0.04 | 0.00 | 0.01 |
| Income | R5 692.85 | R8 082.58 | R4 864.47 | R11 322.81 | R15 978.87 |
| Household size | 4.40 | 4.10 | 4.36 | 3.41 | 3.59 |
| African | 0.75 | 0.72 | 0.82 | 0.75 | 0.45 |
| Coloured | 0.18 | 0.18 | 0.14 | 0.13 | 0.23 |
| Asian | 0.02 | 0.02 | 0.01 | 0.02 | 0.05 |
| White | 0.06 | 0.08 | 0.03 | 0.10 | 0.27 |
| Urban | 0.62 | 0.74 | 0.64 | 0.78 | 0.95 |
| Negative worth | 0.05 | 0.08 | 0.11 | 0.21 | 0.05 |

Source: NIDS 2008-2017, own calculations
Notes: Data from all waves of strongly balanced panel of only employed individuals of working age(15-65)
Data is not weighted

Therefore, as per the discussion by Sweet et al. (2018), it does appear that individuals who acquire informal debt in South Africa exhibit characteristics of more vulnerable individuals. Finally, Table 11, presents the prevalence of depression across the different forms of debt, for all of the demographic characteristics considered.

Once again, we see that the depression prevalence for those with informal debt is much higher than for those with formal debt, while the prevalence of depression does not change too much based on other characteristics. In other words, once there is a trend (e.g. the older population has a higher prevalence of depression compared to the younger demographic), this trend is consistent across debt types. However, the main differences are between those with or without informal debt. Therefore based on these descriptive statistics looking at the prevalence of depression across the different debt categories, we may expect to see that informal debt has a stronger relationship with depression, compared to other forms of debt.

**Table 11: Prevalence of depression by demographic characteristics, for each debt category**

| | All | Formal | Informal | Student | Secure |
|---|---|---|---|---|---|
| **Age** | | | | | |
| 15-17 | 0.15 | - | - | - | - |
| 18-24 | 0.18 | 0.14 | 0.19 | 0.10 | 0.10 |
| 25-34 | 0.17 | 0.14 | 0.21 | 0.13 | 0.10 |
| 35-44 | 0.18 | 0.15 | 0.23 | 0.25 | 0.11 |
| 45-54 | 0.20 | 0.16 | 0.26 | 0.10 | 0.12 |
| 55-65 | 0.20 | 0.14 | 0.24 | 0.06 | 0.10 |
| **Gender** | | | | | |
| Male | 0.16 | 0.13 | 0.21 | 0.10 | 0.09 |
| Female | 0.20 | 0.16 | 0.26 | 0.17 | 0.13 |
| **Couple status** | | | | | |
| Single(widow, divorce, never married) | | | | | |
| Married or living with partner | | | | | |
| **Education** | | | | | |
| No Schooling | 0.26 | 0.21 | 0.20 | 0.00 | 0.00 |
| Primary | 0.23 | 0.18 | 0.31 | 0.29 | 0.23 |
| Highschool no matric | 0.19 | 0.17 | 0.22 | 0.25 | 0.13 |
| Matric | 0.15 | 0.14 | 0.18 | 0.14 | 0.10 |
| Further Education | 0.16 | 0.15 | 0.21 | 0.18 | 0.13 |
| Higher Education | 0.12 | 0.11 | 0.29 | 0.08 | 0.10 |
| **Income from employment** | | | | | |
| R1-R500 | 0.23 | 0.18 | 0.33 | 0.00 | 0.20 |
| R501-R1000 | 0.23 | 0.19 | 0.24 | 0.00 | 0.33 |
| R1001-R2000 | 0.22 | 0.18 | 0.29 | 0.30 | 0.19 |
| R2001-R5000 | 0.17 | 0.17 | 0.20 | 0.10 | 0.17 |
| R5001-R10 000 | 0.13 | 0.14 | 0.21 | 0.11 | 0.14 |
| R10 001-R15 000 | 0.12 | 0.12 | 0.18 | 0.15 | 0.10 |

| | | | | | |
|---|---|---|---|---|---|
| 15 001-R20000 | 0.11 | 0.10 | 0.13 | 0.10 | 0.08 |
| R20001+ | 0.11 | 0.10 | 0.32 | 0.15 | 0.10 |
| **Physical health** | | | | | |
| Fair physical health | 0.18 | 0.15 | 0.22 | 0.14 | 0.11 |
| Bad physical health | 0.41 | 0.33 | 0.43 | 1.00 | 0.19 |
| **Race** | | | | | |
| African | 0.20 | 0.17 | 0.24 | 0.17 | 0.13 |
| Coloured | 0.13 | 0.10 | 0.17 | 0.14 | 0.11 |
| Asian/Indian | 0.13 | 0.12 | 0.09 | - | 0.11 |
| White | 0.09 | 0.08 | 0.28 | 0.00 | 0.08 |
| **Geographical area** | | | | | |
| Rural | 0.20 | 0.15 | 0.22 | 0.20 | 0.16 |
| Urban | 0.17 | 0.15 | 0.24 | 0.13 | 0.11 |
| **Net worth** | | | | | |
| Non-negative | 0.16 | 0.14 | 0.22 | 0.16 | 0.09 |
| Negative | 0.18 | 0.17 | 0.25 | 0.05 | 0.09 |

Source: NIDS 2008-2017, own calculations
Notes: Data from all waves of unbalanced panel
Data is not weighted

## 9. Empirical strategy

### a. Econometric strategy

The econometric models considered for the relationship between debt and depression do so with the lens of an intertemporal approach, building on the life cycle hypothesis framework outlined at the beginning of this paper. This means considering both debt and depression for the individual in the present time period, as well as the previous time period. Moreover, I test for the possibility of a causal relationship between debt and mental health in both directions. To understand the possible causal relationship between debt and depression I employ a number of methods in using the data and data analysis, based on those used in previous literature, in order to increase the level of sophistication of the ultimate possible causal interpretation.

First, I exploit the panel by including lagged variables for both debt and depression, as well as assess the relationship between debt and depression in both directions. Exploiting the panel aspect of the data allows us to examine the dynamics of debt and depression, as well as control for person-specific effects, following a similar approach to that conducted by both Bridges & Disney

(2010), and Keese & Schmitz (2014) in their respective analysis of debt and depression. Secondly, the panel analysis is conducted using fixed effects in order to control for unobserved heterogeneity within the sample, as discussed by Wooldridge (2015). The fixed effects estimation also demeans the data across the years and this is incredibly useful for s panel data analysis when unobserved effects may be present (Wooldridge, 2015). In addition to the measures of control accounting for causality discussed so far, and as per Keese & Schmitz (2014), I use only a subsample of employed individuals to control for possible concerns regarding access to credit across the five waves and thus adding a level of control[9].

As I use indicator variables for both debt and depression, I use a logistic regression to estimate the effects. The logistic regression is a linear probability model which allows us to explain a binary response using regression analysis. Therefore the logistic regression tells us about the changes in the probability of success (y=1) (Wooldridge, 2015). The standard coefficients on the logistic regression present the log-odds of an event occurring. However, these are relatively confusing to interpret and therefore I exponentiate the log-odds coefficients in my analysis to present odds ratios, which I will explain in more detail. However, before I do so, I show my two possible models. The econometric model used in my analysis will analyse the intertemporal effect of debt on depression and vice versa. The primary regression form will be a logistic regression with fixed effects and lagged dependent variables, as well as interaction terms for previous debt and depression. Therefore the final two regressions testing for a possible causal relationship will look as follows:

(1) $Depressed_t = Debt_{t-1} + Debt_{t-1} \times Depressed_{t-1} + Depressed_{t-1} + Debt_t + X_i$

(2) $Debt_t = Deppressed_{t-1} + Debt_{t-1} \times Depressed_{t-1} + Debt_{t-1} + Depressed_t + X_i$

[9] The informal credit market in South Africa, most commonly mashonisas and microlenders still require individuals to be employed, but are less strict on the contract of employmeny or income from employment. Debt from family may be one of the only concerns in my approach, as unemployed individuals may still access loans from friends or family while being unemployed.

It should be noted that in my analysis I build up to these models, showing the effect of including each explanatory variable on the model. I run each of these regressions for each possible category of debt, as described earlier in this paper. Finally, I run this model inclusive of all types of debt in one model, to control for different types of debt.

As mentioned, in my paper I interpret my logistic regressions in terms of odds ratios. The odds ratio is just the exponentiated coefficient of the standard logistic output. As the use of odds ratios to interpret econometric results is not abundant in the literature, I will provide a brief explanation. In simple terms, the odds ratio is the expected number of successes per failure. An odds ratio of 2, therefore, means that for every success of event X, we can expect to see two failures.

### b. Interpreting odds ratios

An odds ratio is calculated as $\frac{p}{(1-p)}$ , where $p$ is the probability of an event occurring. In other words, an odds ratio is the ratio of the probability of an event occurring over the probability that the event does not occur. For example, if the probability of being depressed is 0.2, then the probability of not being depressed is 0.8. Therefore the odds ratio would be $\frac{0.2}{0.8}$ = 0.25. This would be interpreted as: an individual is depressed with 1 in 4 odds, or an odds ratio of 0.25. This is particularly useful when we want to know whether the odds are in favour of an event occurring or not. Based on the equation we can see that the odds are in favour of an event occurring when the odds ratio is above 1, and the odds are not in favour when the ratio is below one. Compared to standard OLS, this is how one distinguishes between a positive or negative effect.

As a coefficient, we can think of the odds ratio as a multiplier to the original odds. For example, consider the following simple logistic model with the coefficient as an odds ratio, as an example:

$$Depressed = 1.2debt + Xi$$

In this model, the coefficient on debt is 1.2. This is interpreted as follows: debt increases the odds of being depressed by a factor of 1.2. Alternatively, this can be interpreted such that debt increases the odds of being depressed by 20%. The odds ratio is beneficial to the analysis as it tells us whether there is an increasing probability (effect) or a decreasing effect, and the magnitude of that effect. Finally, interaction terms in a logistic regression, when interpreting coefficients are calculated as the product of the variables of interest, and not the sum as with linear regression.

## 10. Estimated results

This section presents the results from the fundamental regressions run for the analysis. The section proceeds systematically by first considering the effect of debt on depression, and then continues by discussing the possible impact of depression on acquiring debt. Table 12 presents the four logistic fixed effects estimates of the models investigating the high-level effect of having any debt on the evidence of depressive symptoms. Each estimate is shown in one column, numbered one (1) to (4). The estimates are displayed iteratively and demographic controls are included in all the models. As the intertemporal relationship between debt and depression is being considered, each of the key explanatory variables is added iteratively.

Column 1 shows the only effect of having any debt in the previous period (Any debt (t-1)) on showing evidence of depressive symptoms, without including past period debt or the interaction term. The estimate in column (1) does not show any statistically significant result. However, as I am concerned with the lifetime utility as measured through happiness (or a lack thereof) the full specification in column (4) of Table 12 shows the estimates inclusive of previous depression status, an interaction terms for past debt and depression status (Depressed (t-1) x Any debt (t-1) ), and current debt status (Any debt (t)). The estimates in column (4) of Table 12 show a statistically significant effect of having any debt in the previous period, and the interaction term, on being depressed. More specifically, the odds of being depressed if an individual had debt in the last period increase by 31.5%. However, if one exhibits previous period depression in addition to having debt in the last period, the odds of being depressed decrease by 67.5%.

**Table 12. Logistic fixed effects regressions for the effect of debt on depression**

| Dependent variable: **Depressed$_{(t)}$ = 1** | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Depressed $_{(t-1)}$ = 1 | | 0.168*** | 0.247*** | 0.247*** |
| | | (0.0175) | (0.0307) | (0.0307) |
| Any debt $_{(t-1)}$ = 1 | 1.059 | 1.047 | 1.310** | 1.315** |
| | (0.0909) | (0.0964) | (0.139) | (0.146) |
| Depressed $_{(t-1)}$ x Any debt $_{(t-1)}$ =1 | | | 0.342*** | 0.342*** |
| | | | (0.0758) | (0.0759) |
| Any debt $_{(t)}$ = 1 | | | | 1.011 |
| | | | | (0.102) |
| Observations | 3,503 | 3,432 | 3,432 | 3,430 |

Source: Estimation based on data from NIDS (2008-2017), own calculations
Full regression in Appendix (A2)
Notes: Dependent variable: Depression$_{(t)}$ (CES-D 10 Score>10) =1
Four separate regressions each in their own column from 1 to 4. All regressions are logistic fixed effects

(1) Any debt in previous time period
(2) (1) and previous time period depression status
(3) (2) and an interaction term for previous depression and debt in the previous period
(4) (3) and current period debt status

Additional controls: age, age squared, education, income, marital status, household size, physical health status, geographical location type (urban vs traditional/rural) Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The estimates in Table 12 only show the results from the models including debt as a broad category. However, as previously discussed, different forms of debt have different experiential qualities and play different roles in peoples' lives. Therefore, beginning with the effect of debt on depression, I attempted to understand the role of each debt category on depression. Table 13 presents the estimates of 9 regressions which aim to estimate the effect of debt on depression.

The estimates displayed from columns 1 to 9 vary by adding various elements of control. The differences between each of the models are summarised by the checkboxes at the bottom of Table 13 which display the properties of the table, to allow for easy comparison. The checkboxes show whether the model has fixed effects, lagged debt variables, a lagged depression variable, and a control variable indicating whether an individual reports having a one-shot negative net worth to allude to possible over-indebtedness. Columns 1 and 2 in Table 13 present a simplified, standard logit model, without fixed effects to first assess the associative relationship between debt and depression without controlling for unobserved heterogeneity.

The estimates in column 1 only present the effect of current period debt on depression. At the associative level, we observe a negative association between formal debt and depression while observing a positive association between informal debt and depression. This means that informal debt may increase the odds of becoming depressed, while formal debt may decrease the odds of becoming depressed. Including the lagged variables (column 2) of the debt categories does not affect the direction of the relationship between any of the significant results from column one. While there are some changes in the magnitude of the odds, the key difference observed in column 2 is that previous informal debt informal debt (t-1) has a statically significant positive association between debt and depression. Therefore, the estimates in the associative relationship, taking the regression in column 2 as the stronger model owing to the intertemporal dynamic, show that the odds of entering into depression increase by a factor of 1.5 if one has informal debt in the current, and also 1.5 if one acquired informal debt in the previous period, each of these are the change in odds compared to individuals without informal debt. Formal debt decreases the odds of becoming depressed, compared to individuals without any formal debt, by approximately 11%.

Moving to the fixed effects models, column 3 does not include any lagged variables, the significance of the coefficients on current period debt disappears. However, once the lagged variables for debt are re-introduced, the significance on the coefficient on current and previous period informal debt return to being statistically significant, for the remaining models until column 9, provided both informal debt variables are included in the model. Moving to column 5, introducing an indicator for negative net worth significantly increases the significance and magnitude on the coefficient between informal debt and depression, when compared to the similar model without negative worth in column 3. This suggests that negative net worth is related to informal debt in a meaningful enough way to have a substantial effect on the coefficient.

Once the lagged variables for debt are re-introduced in column 7, we observe a significant increase in the coefficient on the odds of becoming showing evidence of depressive symptoms from acquiring informal debt. Without yet controlling for depression in the previous period, the odds of becoming depressed from the current period informal debt increase by a factor of 2.7, compared to individuals without the current period informal debt. Furthermore, individuals with previous period informal debt exhibit a change in the odds of depression by a factor of 1.8. The estimates in column 8 report the results without controlling for individual negative net worth. Interestingly, current period student debt changes to be statistically significant, increasing the odds of becoming depressed by a factor of 2.47.

Once controlling for negative net worth, as presented in column 9, most of the statistical significance on student debt is lost, and the only statistically significant estimates are of the coefficients on informal debt – for both periods. Column 9 presents the estimates once all controls specified for Table 13 are accounted for, including the lagged debt and depression variables, and an indicator for negative net worth. The estimates show that having informal debt in the current period increases the odds of becoming depressed in the current period by 132.4% compared to individuals without informal debt in the current period. Having informal debt in the previous period increases the odds of becoming depressing in the current period by 94.5%, compared to individuals without any informal debt in the last period.

**Table 13. Logistic regression estimates presenting the effect of different categories of debt on depression, with all debt categories included in the model**

Dependent variable: **Depressed$_{(t)}$ = 1**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Formal debt $_{(t)}$ = 1 | 0.876*** | 0.890** | 0.932 | 1.014 | 0.972 | 0.892 | 1.047 | 1.062 | 0.878 |
| | (0.0402) | (0.0505) | (0.0622) | (0.0918) | (0.130) | (0.140) | (0.0994) | (0.110) | (0.165) |
| Informal debt $_{(t)}$ = 1 | 1.360*** | 1.501*** | 1.160 | 1.482** | 1.844*** | 2.702*** | 1.183 | 1.386* | 2.324*** |
| | (0.107) | (0.138) | (0.131) | (0.232) | (0.395) | (0.757) | (0.185) | (0.245) | (0.661) |
| Student debt $_{(t)}$ = 1 | 0.937 | 1.117 | 1.335 | 2.257 | 1.046 | 1.288 | 2.245 | 2.470* | 2.571 |
| | (0.203) | (0.306) | (0.412) | (1.162) | (0.717) | (1.001) | (1.139) | (1.259) | (3.021) |
| Secure debt $_{(t)}$ = 1 | 1.006 | 0.852 | 0.791 | 0.841 | 1.275 | 1.326 | 0.701 | 0.651 | 0.939 |
| | (0.105) | (0.141) | (0.131) | (0.217) | (0.496) | (0.575) | (0.193) | (0.190) | (0.454) |
| Formal debt $_{(t)}$ = 1 | | 0.982 | | 1.020 | | 0.998 | | 1.058 | 1.011 |
| | | (0.0591) | | (0.0933) | | (0.155) | | (0.109) | (0.179) |
| Informal debt $_{(t-1)}$ = 1 | | 1.219* | | 1.507** | | 1.818* | | 1.688*** | 1.945* |
| | | (0.134) | | (0.261) | | (0.611) | | (0.335) | (0.736) |
| Student debt $_{(t-1)}$ = 1 | | 0.681 | | 0.953 | | 1.174 | | 1.463 | 1.637 |
| | | (0.205) | | (0.410) | | (1.005) | | (0.702) | (1.532) |
| Secure debt $_{(t-1)}$ = 1 | | 1.173 | | 0.922 | | 0.760 | | 0.674 | 0.577 |
| | | (0.187) | | (0.221) | | (0.317) | | (0.178) | (0.249) |
| Negative net worth = 1 | | | | | 1.821** | 1.745* | | | 2.225*** |
| | | | | | (0.481) | (0.525) | | | (0.667) |
| Depressed $_{(t-1)}$ = 1 | | | | | | | 0.164*** | 0.159*** | 0.152*** |
| | | | | | | | (0.0177) | (0.0176) | (0.0325) |
| Constant | 0.401** | 0.250*** | | | | | | | |
| | (0.144) | (0.118) | | | | | | | |
| Observations | 18,182 | 12,207 | 6,254 | 3,416 | 1,422 | 1,147 | 3,382 | 3,345 | 1,130 |
| Number of individuals | 8,216 | 6,333 | | | | | | | |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| FE | | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged debt | | ✓ | | ✓ | | ✓ | | ✓ | ✓ |
| Negative net worth | | | | | ✓ | ✓ | | | ✓ |
| Lagged depression | | | | | | | ✓ | ✓ | ✓ |

Source: Estimation based on data from NIDS (2008-2017), own calculations

Full regression in Appendix (A3)
Notes: Dependent variable: Depression$_{(t)}$ (CES-D 10 Score>10) =1
Additional controls: age, age squared, education, income, marital status, household size, physical health status, geographical location type (urban vs traditional/rural) Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 13 is useful for the analysis as it presents the effects of controlling for unobserved heterogeneity by including fixed effects, as well as the effect of exploiting the panel through the use of lagged debt and depression variables. In addition, the inclusion of the signal of over-indebtedness (negative net worth) into the model, provides as an additional control for the possible magnitude of debt. However, the estimates also control for all of the different types of debt. Because of the large number of debt controls, we don't necessarily see the effect of one particular type of debt on depression. Therefore, as each category of debt may affect different individuals, Table 14 presents the estimates looking at each category of debt independently.

There are 10 independently estimated fixed effects logistic regressions in Table 14, with each pair of regressions presenting only the effect of one category of debt, without controlling for other debt categories in the same model. Each regression includes a lagged variable for depression, a lagged variable for the type of debt in the model, as well as the interaction term for having both depression and a particular type of debt. This regression is run twice for each type of debt, with the second regression for each type of debt including the indicator for current indebtedness. The first set of estimates in Table 14, presented in columns 1 and 2 show the effect of having any debt, similar to the estimates in Table 12, allowing for easy comparison.

The remaining estimates, from columns 3 to 10 present the estimates for each type of debt, as independently run models. The results in Table 14 are reported as follows: once controlling for formal debt in the current period, formal debt in the previous period increases the odds of being depressed in the current period, compared to individuals without formal debt in the previous period by a factor of 1.282, associated with a 28.2% increase in the odds of being depressed in the current period. The interaction term on formal debt and depression in the previous period can be interpreted as the product of the coefficient on the interaction term and having formal debt in the previous period. Therefore, the if an individual was depressed in the previous period, then the effect of having formal debt is a change in the odds of being depressed in the current period by 0.465, compared to individuals who were not depressed and did not have debt in the previous period. Therefore, given the estimate on the effect of formal debt with previous depression is associated with a 53.5% decrease in the odds of being depressed in the current period.

The coefficients on informal debt in columns 5 and 6 of Table 14 are consistent with the results observed so far that informal debt negatively affects mental health by increasing the odds of becoming depressed. The coefficient on informal debt in t-1, when estimated independently of having other categories of debt, tell us that informal debt in the previous period increases the odds of current period  debt by 97%, when controlling for current period informal debt, and increases the odds of current period depression by 72.2%, compared to individuals without any informal debt in the previous period. Without controlling for current period depression, the interaction term on *Depressed* $_{(t-1)}$ *x has debt* $_{(t-1)}$ combines with the coefficient of *Has debt* $_{(t-1)}$ to create combined effect of 0.926, associated with a 7.4% decrease in the odds of being depressed in the current period. However, once controlling for informal debt in the current period (column 6), the interaction term on informal debt and being depressed in t-1 tells gives an odds ratio of 1.0638, a 6.38% increase in the odds of being depressed compared to non-debtors without depression in the previous period. Furthermore, controlling for current period informal debt, the coefficient on current period informal debt is associated with a 39% increase in the odds of becoming depressed.

Finally, the last significant coefficient in Table 14 is that on current period student debt which is associated with a 144% increase in the odds of being depressed in the current period.

**Table 14. Logistic regression estimates presenting the effect of independently run regression reporting the effect of each type of debt on depression**

| Dependent variable: **Depressed$_{(t)}$ = 1** | All debt | | Formal debt | | Informal debt | | Student debt | | Secure debt | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Depressed$_{(t-1)}$ = 1 | 0.247*** | 0.247*** | 0.228*** | 0.227*** | 0.174*** | 0.174*** | 0.167*** | 0.168*** | 0.169*** | 0.165*** |
| | (0.0307) | (0.0307) | (0.0270) | (0.0271) | (0.0190) | (0.0190) | (0.0176) | (0.0177) | (0.0181) | (0.0179) |
| Has debt $_{(t-1)}$ = 1 | 1.310** | 1.315** | 1.252** | 1.282** | 1.722** | 1.970*** | 1.406 | 1.738 | 0.770 | 0.722 |
| | (0.139) | (0.146) | (0.135) | (0.146) | (0.388) | (0.488) | (0.760) | (1.125) | (0.204) | (0.201) |
| Depressed $_{(t-1)}$ x has debt $_{(t-1)}$ =1 | 0.342*** | 0.342*** | 0.365*** | 0.363*** | 0.538* | 0.540* | 0.444 | 0.562 | 0.722 | 0.670 |
| | (0.0758) | (0.0759) | (0.0809) | (0.0808) | (0.198) | (0.194) | (0.336) | (0.463) | (0.334) | (0.318) |
| Has debt $_{(t)}$ = 1 | | 1.011 | | 1.059 | | 1.390* | | 2.444* | | 0.649 |
| | | (0.102) | | (0.108) | | (0.248) | | (1.255) | | (0.192) |
| Observations | 3,432 | 3,430 | 3,422 | 3,404 | 3,405 | 3,396 | 3,421 | 3,404 | 3,427 | 3,422 |

Source: Estimation based on data from NIDS (2008-2017), own calculations
Full regression in Appendix (A4)
Notes: Dependent variable: Depression$_{(t)}$ (CES-D 10 Score>10) =1
Additional controls: age, age squared, education, income, marital status, household size, physical health status, geographical location type (urban vs traditional/rural) Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Bringing together all of the information in Table 14, it is clear that considering current period indebtedness is important to the interpretation of the final coefficients. Therefore, in light of using the life cycle model as a framework for this analysis, the relevant models are only those including depression and debt in both periods, as my analysis is concerned with the lifetime relationship between debt and depression. Summarising the results from Table 14, at the individual debt category level, previous period formal debt and informal debt results present an increase in the odds of being depressed in the current period. Being depressed and having formal debt in the previous period decreases the degree to which the odds of being depressed increases; however, for informal debt, there is a persistent increase in the odds of being depressed across the individual's inter-temporal debt journey. Finally, current student debt exhibits a high increase in the odds of being depressed in the current period[10].

[10] However, I have not controlled for whether an individual is currently studying. As my analysis only looks at a sub sample of employed individuals. We may expect that if an individual has student debt, is studying and employed simultaneously, this may have significant effects on the

The final regression estimating the effect(s) of debt on depression is presented in Table 15. Consolidating the estimates reported from Table 12 until Table 14, the following can be said about the relationship between debt and depression. Firstly, Table 12 shows a statistically significant increase in the odds of being depressed based on having any debt in the previous period, and that there is a statistically significant relationship between having any debt and being depressed in the previous period. Following this, Tables 13 and 14 unpack the effect of each independent debt category on being depressed. The results consistently show that informal debt in both the previous period and the current period increases the odds of being depressed. The results in Table 13 also demonstrate that negative net worth may play a key role in the explanation of the debt categories. Following this, Table 14 estimates each of the debt categories' effect on depression independently, once again showing negative mental health consequences from informal debt, and possible negative mental health effects from formal debt, as well as student debt.

The final set estimates reported in Table 15, presents 4 separate regressions which include controls for all debt categories discussed above, while separate regressions comparing standard logistic estimates to the fixed effects estimates. These estimates are then compared based on their proxy for over-indebtedness (negative net worth). Columns 1 and 2 in Table 15 present the estimates without controlling for negative net worth. Column 1 presents the standard logistic model estimates, without fixed effects. Moving from Column 1 to column 2 we see that without fixed effects a statistically significant relationship exists between debt and current period formal debt, current period informal debt, and current period student debt. The association in the standard model shows that an individual with a previous period student debt is associated with a 44.9% decrease in the odds of being depressed. In the standard logistic model, without controlling for negative net worth (column 1) current period formal debt is associated with a 17.8% decrease in the odds of being depressed, and current informal debt increase the odds of being depressed by 49.5%. However, once controlling for unobserved heterogeneity by employing fixed effects, current period informal debt, previous period informal debt, previous period informal debt increase the odds of being depressed in the current period, while the interaction terms for a previous period

individual's mental health. The exclusion of current period education status is a limitation of this analysis, but should be explored in the future.

informal debt and formal debt exhibit statistically significant results, presenting a decrease in the odds of being depressed in the current period.

Moving to column 3, the standard logistic regression estimates controlling for negative net worth, but without fixed effects, are presented. Controlling for negative net worth, when compared to column 1, we can see that the coefficients tell a similar story in that current period formal debt is associated with a decrease in the odds of being depressed by ~12%, and current period informal debt increases the odds of being depressed by 59.5%. However, compared to column 1, column 3 has no statistically significant estimates on student debt.

Finally, column 4 presents the estimates of the logistic model with fixed effects, including all the controls across debt categories, where the fixed effects to control for within-person specific effects. The column 4 estimates present that informal debt in the current period increases the odds of being depressed by a factor of 2.268, this is associated with 126.8% increase in the odds of being depressed, compared to individuals without informal debt in the current period. The second statistically significant result reported in column 4 is that previous period informal debt is associated with a 197.5% increase in the odds of being depressed in the current period. Thirdly, having formal debt and being depressed in the previous period is associated with a 78.8% decrease in the odds of being depressed.

However, this has to be interpreted as an interaction and is, therefore, multiplying the odds ratios we get a combined odds ratio of 0.296, interpreted as 70.4% decrease in the odds of being depressed in the current period. Finally, and interestingly previous period secure debt is associated with a 54.2% decrease in the odds of being depressed. From the estimates reported in Tables 12 to 15, this is the first regression to report a statically significant relationship on one of the variables related to secure debt.

**Table 15. Standard logistic and fixed effects logistic estimates for including all debt categories**

| Dependent variable: **Depressed$_{(t)}$ = 1** | | | | |
|---|---|---|---|---|
| | Logistic | Fixed effects | Logistic | Fixed Effects |
| | (1) | (2) | (3) | (4) |
| Depressed$_{(t-1)}$ = 1 | 1.001 | 0.229*** | 0.964 | 0.271*** |
| | (0.0827) | (0.0293) | (0.108) | (0.0658) |
| Formal debt $_{(t)}$ = 1 | 0.882** | 1.042 | 0.879* | 0.869 |
| | (0.0503) | (0.109) | (0.0680) | (0.168) |
| Informal debt $_{(t)}$ = 1 | 1.495*** | 1.398* | 1.595*** | 2.268*** |
| | (0.138) | (0.252) | (0.183) | (0.674) |
| Student debt $_{(t)}$ = 1 | 1.154 | 2.362 | 0.860 | 2.378 |
| | (0.316) | (1.259) | (0.310) | (2.605) |
| Secure debt $_{(t)}$ = 1 | 0.857 | 0.649 | 0.935 | 0.922 |
| | (0.142) | (0.197) | (0.202) | (0.462) |
| Formal debt $_{(t-1)}$ = 1 | 0.998 | 1.288** | 0.960 | 1.399 |
| | (0.0652) | (0.150) | (0.0828) | (0.287) |
| Informal debt $_{(t-1)}$ = 1 | 1.179 | 2.038*** | 1.200 | 2.975** |
| | (0.149) | (0.501) | (0.197) | (1.479) |
| Student debt $_{(t-1)}$ = 1 | 0.551* | 1.604 | 0.509 | 1.080 |
| | (0.196) | (1.024) | (0.246) | (1.384) |
| Secure debt $_{(t-1)}$ = 1 | 1.219 | 0.643 | 0.947 | 0.458* |
| | (0.202) | (0.181) | (0.211) | (0.210) |
| Depressed $_{(t-1)}$ x Formal debt $_{(t-1)}$ =1 | 0.958 | 0.370*** | 0.879 | 0.212*** |
| | (0.142) | (0.0856) | (0.177) | (0.0913) |
| Depressed $_{(t-1)}$ x Informal debt $_{(t-1)}$ =1 | 1.085 | 0.519* | 0.707 | 0.351 |
| | (0.289) | (0.204) | (0.289) | (0.226) |
| Depressed $_{(t-1)}$ x Student debt $_{(t-1)}$ =1 | 2.759 | 1.188 | 3.799 | 5.228 |
| | (1.864) | (0.978) | (3.817) | (7.693) |
| Depressed $_{(t-1)}$ x Secure debt $_{(t-1)}$ =1 | 0.760 | 0.890 | 1.310 | 2.803 |
| | (0.315) | (0.433) | (0.632) | (2.194) |
| Negative net worth = 1 | | | 1.197 | 2.597*** |
| | | | (0.179) | (0.864) |
| Constant | 0.251*** | | 0.226** | |
| | (0.120) | | (0.147) | |
| Observations | 12,045 | 3,345 | 7,209 | 1,130 |
| Number of pid | 6,293 | | 4,944 | |

Source: Estimation based on data from NIDS (2008-2017), own calculations
Full regression in Appendix (A5)
Notes: Dependent variable: Depression$_{(t)}$ (CES-D 10 Score>10) =1
Additional controls: age, age squared, education, income, marital status, household size, physical health status, geographical location type (urban vs traditional/rural) Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

So far, Tables 12 to 15 have presented the estimates for the effect of debt on being depressed in the lifecycle of the individual. However, as this paper is concerned with the possible bi-directional causal relationship between debt and depression, Tables 16 and 17 investigate the possible effect of being depressed on acquiring debt. Table 16 presents the logistic fixed effects estimates on the effect of being depressed on having any debt over the individual's lifecycle, without categorising the debt. The table consists of four separately run regressions, moving from column 1 to column 4, each introducing additional elements of the lifecycle into the model, in order to understand the effect of including each variable on the estimates. Column 1 shows only the effect of being depressed on having any debt – no statistically significant relationship is observed. Similarly once adding having any debt in the previous period (column 2), no statistically significant relationship is observed. Once adding the interaction term for having any debt and being depressed in the previous period, we see that the combined interaction term and effect of being depressed is 1.16, indicating a 16% increase in the odds of having any debt. Finally, once controlling for current period depression (column 4), the total interaction effect, calculated by multiplying the odds ratios, is associated with a 12% increase in having any debt in the current period.

**Table 16. Logistic fixed effects regressions for the effect of depression on having debt**

| Dependent variable: **Any debt $_{(t)}$ = 1** | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Depressed $_{(t-1)}$ = 1 | 1.033 | 0.952 | 0.838 | 0.818* |
| | (0.0853) | (0.0853) | (0.0929) | (0.0941) |
| Any debt $_{(t-1)}$ = 1 | | 0.220*** | 0.207*** | 0.207*** |
| | | (0.0170) | (0.0176) | (0.0177) |
| Depressed $_{(t-1)}$ x Any debt $_{(t-1)}$ =1 | | | 1.393* | 1.374* |
| | | | (0.264) | (0.265) |
| Depressed $_{(t)}$ = 1 | | | | 0.978 |
| | | | | (0.0964) |

| | | | | |
|---|---|---|---|---|
| Observations | 4,948 | 4,948 | 4,948 | 4,869 |

Source: Estimation based on data from NIDS (2008-2017), own calculations
Full regression in Appendix (A6)
Notes: Dependent variable: Any debt$_{(t)}$ (formal, informal, student, or secure)=1
Four separate regressions each in their own column from 1 to 4. All regressions are logistic fixed effects
(1) Depression
(2) (1) and previous time period debt
(3) (2) and an interaction term for previous depression and debt in the previous period
(4) (3) and current period depression status
Additional controls: age, age squared, education, income, marital status, household size, physical health status, geographical location type (urban vs traditional/rural) Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

However, as with the approach when looking at the effect of having debt on being depressed, the possible different experiential qualities and needs associated with each category of debt may vary. Therefore, Table 17 presents the logistic fixed effects estimates for 8 separate regressions, with each alternating column including a control for current period depression. Columns 1 and 2 repeat the last two columns reported in Table 16 for comparison. Columns 3 and 4 present the estimates of the effect of being depressed on having formal debt with no statistically significant results.

Columns 5 and 6 show the effect that depression has on having debt. We can see that before controlling for current period depression, there is a statistically significant odds ratio of 0.744 on being depressed in the previous period, associated with a 26.6% decrease in the odds of having formal debt. However, once controlling for current period depression, there is no statistically significant effect from previous period depression. Instead, current period depression is statistically significant at the 10% level, indicating a 42% increase in the odds of having formal debt if one reports being depressed in the current period. Finally, there is no statistically significant effect of having secure debt on being depressed. The effect of depression on student debt could not be estimated owing to the small sample size.

**Table 17. Logistic fixed effects regressions for the effect of being depressed on having each type of debt**

| Dependent variable(s): **Has debt $_{(t)}$ = 1** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Any debt | | Formal debt | | Informal debt | | Secure debt | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Depressed(t) =1 | | 0.978 | | 0.998 | | 1.428* | | 0.870 |
| | | (0.0964) | | (0.101) | | (0.261) | | (0.242) |
| Depressed $_{(t-1)}$ = 1 | 0.838 | 0.818* | 0.882 | 0.872 | 0.744* | 0.772 | 1.221 | 1.174 |
| | (0.0929) | (0.0941) | (0.101) | (0.104) | (0.132) | (0.151) | (0.423) | (0.441) |
| Has debt $_{(t-1)}$ = 1 | 0.207*** | 0.207*** | 0.220*** | 0.221*** | 0.0694*** | 0.0633*** | 0.376*** | 0.379*** |
| | (0.0176) | (0.0177) | (0.0190) | (0.0191) | (0.0179) | (0.0170) | (0.0731) | (0.0741) |
| Depressed $_{(t-1)}$ x Has debt $_{(t-1)}$ =1 | 1.393* | 1.374* | 1.295 | 1.287 | 1.471 | 1.442 | 0.650 | 0.646 |
| | (0.264) | (0.265) | (0.248) | (0.249) | (0.775) | (0.787) | (0.371) | (0.370) |
| Observations | 4,948 | 4,869 | 4,724 | 4,645 | 1,408 | 1,386 | 660 | 655 |

Source: Estimation based on data from NIDS (2008-2017), own calculations
Full regression in Appendix (A7)
Additional controls: age, age squared, education, income, marital status, household size, physical health status, geographical location type (urban vs traditional/rural) Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

### 11. Discussion

Beginning with the effect of having debt on depression, the following results emerge. Firstly, there is statistically significant evidence that informal debt has a worsening effect on depression, when looking at the effect of debt on being depressed. Quantifying this relationship, individuals who previously reported having debt through the informal lending market exhibited an increase in the odds of being depressed by a factor of 2.974. This means that, holding everything else equal, the odds of being depressed increase by 197.4% for individuals reporting previous period debt. An explanation for why this percentage increase in the odds is so much larger, could be that formally employed people who acquire informal credit may be more likely to have more 'problem debt' and therefore cannot obtain formal credit. Moreover, there is evidence that current period informal debt increases the odds of depression in the current period. The results of informal debt presented in my analysis in Section 10 are similar to those reported by Sweet et al. (2018) in that individuals with informal debt are more likely to report poorer mental health. However, in the Sweet et al. (2018) findings informal debt is more specifically payday lenders or lenders who use vehicle collateral from consumers in order to secure their credit. However, in my analysis informal debt also included loans from employers, family or friends, outstanding tax debt – while still including microlenders and mashonisas (similar to the Sweet et al. (2018) data).

The second interesting result found in my analysis is that long term secure debt i.e. having secure debt in the previous period, decreases the odds of being depressed in the current period by 54.2%. However, we don't observe the possible effect of not being able to meet payments and the stress associated with this. Therefore, this is not comparable to the results given in the previous work on secure debt and depression (Gathergood, 2012) (Bridges & Disney, 2010).

Thirdly, individuals who acquired formal debt in the past, but were also depressed are associated with a lower odds of being depressed in the current period by 70.4% compared to individuals without formal debt who were also not depressed in the former period. As discussed by Eyal (2016) depression is not a permanent state, but individuals can shift between states of depression. Therefore, this results on the interaction effect of previous formal debt and depression should be approached with caution, given that neither of the other variables regarding formal debt are statistically significant.

Fourth, there appears to be a possible bi-directional causal relationship between current informal indebtedness and depression. Based on the analysis in Section 10, the data suggest that being depressed in the current period increases the odds of acquiring informal debt by 42.8%. Similarly being in debt in the current period increases the odds of being depressed by 126.8%, based on this there is likely a possible bi-directional causal link. However, with regards to long term utility, entering into informal debt has a long term effect on depression by increasing the odds of being depressed in the next period by 197.5%.  Therefore, in the intertemporal model, it is possible that being depressed may lead to acquiring informal debt, and that this acquisition of informal debt has long term effects on mental health.

## 12. Robustness checks used and limitations

Multiple methods to check for robustness were used during the analysis of the panel, including using a balanced panel, exploiting the dataset and limiting the population to only employed individuals. However, some robustness checks remain. This section discusses further robustness checks, as well as the limitations of the analysis. However, one of the possible concerns is that individuals who are severely depressed or severely indebted do not always answer the questions and are therefore undersampled. This means that there could be non-random missing data. Therefore, to check if this is the case, I present Table 18 which compares the full sample, those with missing depression data, and those with missing debt data. The data presented in Table 18 suggests that individuals who report missing data for both debt and depression appear to have relatively similar mean demographic characteristics such as income, education, marital status.

Yet, large differences are observed between the mean debt population for the prevalence of depression (32 percentage points greater for those with missing debt data), and the prevalence of negative net worth which for those with missing debt data displayed a prevalence of 50% - strongly suggesting that overindebted individuals do not report debt details at the component level. Moreover, the similarity in demographic characteristics raises suspicion as to whether it is a similar sample who do not report information on both characteristics. To see if this was true, I looked at whether the same individuals do not respond to questions on debt and depression. The final column in Table 18 indicates that similar individuals do not respond to questions on debt and depression with 99% of individuals who don't report debt data also not reporting depression data[11].

Following Table 18, there seems to be evidence that the sample underestimates the relationship between debt and depression for individuals who are likely to be depressed, as well as individuals who are likely to be over-indebted (if we assume that negative net worth is a suitable proxy for over-indebtedness). The implication of this is that we may underestimate the effect of debt on depression.

[11] The non-response may be a general trend for these individuals throughout the questionnaire. However, I do not check for this in my robustness check.

**Table 18. Mean demographic characteristics of sample comparing possible missing data sample groups**

| Variables | Mean | Missing CES-D 10 | Missing debt data | Missing debt and depression data |
|---|---|---|---|---|
| Depressed (CESD-10 >10) | 0.18 | - | 0.50 | - |
| CES-D 10 | 6.65 | - | 10.75 | - |
| Age | 38.12 | 37.44 | 37.55 | 37.54 |
| Female | 0.49 | 0.33 | 0.30 | 0.30 |
| Married or living together | 0.43 | 0.42 | 0.42 | 0.42 |
| Years of education | 9.65 | 10.04 | 10.13 | 10.12 |
| Bad physical health | 0.02 | 0.02 | 0.02 | 0.02 |
| Total income | R5 692.85 | R6 245.04 | R6 430.85 | 6402.11 |
| Household size | 4.40 | 5.12 | 5.23 | 5.23 |
| African | 0.75 | 0.66 | 0.63 | 0.63 |
| Coloured | 0.18 | 0.21 | 0.22 | 0.22 |
| Asian | 0.02 | 0.03 | 0.03 | 0.03 |
| White | 0.06 | 0.10 | 0.12 | 0.12 |
| Urban | 0.62 | 0.64 | 0.64 | 0.64 |
| Negative net worth | 0.05 | 0.07 | 0.50 | - |
| ***Overall N*** | **24 902** | **1,845** | **1,532** | **1,528** |

Source: NIDS 2008-2017, own calculations
Notes: Data from all waves of strongly balanced panel of only employed individuals of working age(15-65)

There are two primary further limitations of my analysis. Firstly, while depression is reported in the analysis, some prior literature captures information regarding the possible cause of depression. More specifically, this includes information on debt stress in questions asking whether an individual feels financially stressed. Thus, I cannot directly compare my results to those of Bridges & Disney (2010) who argue that debt stress is a function of one's pre-existing mental health status .i.e. individuals with previous mental health issues are more likely to report debt stress, but are not necessarily more likely to have objective debt problems compared to individuals who do not report debt stress.

Secondly, I do not report how the value of debt affects mental health. This means that while we can compare debtors to non-debtors, I cannot comment on the true degree to which debt affects mental health if it is conditional on the debt value, as it has been found in previous research (Richardson, Elliott, & Roberts, 2013). The lack of considering the value of debt also means that I do not consider how the debt to income ratio effects mental health. Thirdly, in an ideal world we would include an instrumental variable that can function as a measure to better state causality, compared to the lagged variables used in my model. While lagged variables have been used in the past as substitutes for instrumental variables, a real instrumental variable which displays exogenous variation in either debt or depression may guide us to a more sophisticated result. Using an instrumental variable may be easier when investigating debt values, as one can follow the approach as per Gathergood (2012) and use variation in local level housing prices. Fourth, a possible endogeneity problems still remains. There may be some omitted variable bias with some key confounding factors of debt and depression, the outcome of which may lead to bias and inconsistent estimators.

Finally, areas of future research should consider the debt value-level data, such as exploring the effect of a change in the debt to income ration on being depressed, or vice versa. Additionally, changes in short term debt may not be well captured through the panel data. For example, an individual could go into certain types of debt or become overindebted for short period of time, causing changes in mental health, or individuals who experience short term changes in mental health may change their consumption patterns – investigating this relationship on a more day to day level would be very interesting. Finally, a comprehensive comparison with other measures of well-being should also be considered in order to make our understanding of the relationship between debt and depression, or mental health more broadly, more robust.

## 13. Concluding remarks

This research set out to examine the causal relationship between debt and depression in South Africa, based on the data captured in the NIDS. While it has been established that there is a positive link between income and subjective well-being, the role of debt in an individual's financial portfolio, and the mechanism through which debt affects subjective well-being is not well understood. According to traditional economic models such as Dynamic Consumption Theory, debt can be used to increase utility by allowing individuals to increase their marginal utility of consumption over time. However, the traditional model does not consider the possible effect of debt stress in the utility equation.

The relationship between debt and depression is an emerging field of research, and not much research has been conducted on the topic. Furthermore, almost all the existing research on the matter is done in developed or Western economies, where dynamics of poverty and inequality are not as severe as those in South Africa. Therefore, a key contribution of this paper is to understand the relationship between debt and depression in a developing economies context.

To understand the possibility of a causal relationship between debt and depression, I exploited a subsample of constantly employed individuals from the panel dataset of the NIDS between 2008 and 2017, as per the methodology in Keese & Schmitz (2014). The panel nature of the dataset allowed me to apply a fixed effects analysis and include a dynamic model to control for individual-level heterogeneity and within person-specific effects. The final results from the model can be described as follows: Individuals who acquire informal debt have an increase in the odds of being depressed in both the current and future period. On the other hand, individuals who are depressed have an increase in the odds of being depressed. Therefore, informal debt appears to exhibit a bi-directional causal relationship. Furthermore, individuals with secure or mortgage debt exhibit a decrease in the odds of being depressed in the future. Finally, there is evidence that acquiring formal debt and being depressed decreases the odds by which an individual exhibits symptoms of depression in the future.

That said, several pertinent issues of this analysis were highlighted. The most alarming of which is the possible endogeneity between current period informal debt and current period evidence of depressive symptoms, which may be considered as a bi-directional causal relationship, although asserting this as a fact should be approached with heavy caution. Future research which aims to identify a causal relationship between debt and depression should more carefully consider the use of an instrumental variable as an accurate source of exogenous variation, reducing the possible concerns of endogeneity. Overall, as an increasing quantity of research is conducted on the relationship between mental health and debt, we can start to build a framework through which this dynamic can be better understood, hopefully leading to net increases in utility across the board.

**Reference List**

Achtziger, A., Hubert, M., Kenning, P., Raab, G. & Reisch, L. 2015. Debt out of control: The links between self-control, compulsive buying, and real debts. Journal of Economic Psychology. 49:141-149.

Ando, A. & Modigliani, F. 1963. The" life cycle" hypothesis of saving: Aggregate implications and tests. The American Economic Review. 53(1):55-84.

Ardington, C. & Case, A. 2010. Interactions between mental health and socioeconomic status in the South African national income dynamics study. Tydskrif Vir Studies in Ekonomie En Ekonometrie= Journal for Studies in Economics and Econometrics. 34(3):69.

Baron, E.C., Davies, T. & Lund, C. 2017. Validation of the 10-item centre for epidemiological studies depression scale (CES-D-10) in Zulu, Xhosa and Afrikaans populations in South Africa. BMC Psychiatry. 17(1):6.

Berger, L.M., Collins, J.M. & Cuesta, L. 2016. Household debt and adult depressive symptoms in the United States. *Journal of Family and Economic Issues*. 37(1):42-57.

Bridges, S. & Disney, R. 2010. Debt and depression. *Journal of Health Economics*. 29(3):388-403.

Brown, S. & Gray, D. 2016. Household finances and well-being in Australia: An empirical analysis of comparison effects. *Journal of Economic Psychology*. 53:17-36.

Brown, S., Taylor, K. & Price, S.W. 2005. Debt and distress: Evaluating the psychological cost of credit. *Journal of Economic Psychology*. 26(5):642-663.

Caputo, R.K. 2012. Patterns and predictors of debt: A panel study, 1985-2008. J.Soc.& Soc.Welfare. 39:7.

Choonoo, S. 2016. No title. Developments in the South African Credit Market and Analysis on Indebted Consumers using NIDS Data.

Clark, A.E. 2003. Unemployment as a social norm: Psychological evidence from panel data. *Journal of Labor Economics*. 21(2):323-351.

Clark, A.E., Frijters, P. & Shields, M.A. 2008. Relative income, happiness, and utility: An explanation for the Easterlin paradox and other puzzles. *Journal of Economic Literature*. 46(1):95-144.

Clayton, M., Liñares-Zegarra, J. & Wilson, J.O. 2015. Does debt affect health? Cross country evidence on the debt-health nexus. *Social Science & Medicine*. 130:51-58.

Cooke, R., Barkham, M., Audin, K., Bradley, M. & Davy, J. 2004. Student debt and its relation to student mental health. *Journal of further and Higher Education*. 28(1):53-66.

Currie, J. & Tekin, E. 2015. Is there a link between foreclosure and health? *American Economic Journal: Economic Policy*. 7(1):63-94.

Daniels, R. and Augustine, T., 2016. The measurement and distribution of household wealth in South Africa using the National Income Dynamics Study (NIDS) Wave 4.

Das, J., Do, Q.-T., Friedman, J., McKenzie, D. & Scott, K. (2007), 'Mental health and poverty in developing countries: revisiting the relationship', *Social Science and Medicine* 65(3), 467 – 480.

Davel, G. 2013. Regulatory options to curb debt stress. Focus Note. 83.

Davis, H.W.C. 1920. Aristotle's politics. At the Clarendon Press. Available: .

Deaton, A. 2005. Franco Modigliani and the Life Cycle Theory of Consumption. Available at SSRN: https://ssrn.com/abstract=686475 or http://dx.doi.org/10.2139/ssrn.686475

Dellande, S., Gilly, M.C. & Graham, J.L. 2016. Managing consumer debt: Culture, compliance, and completion. *Journal of Business Research*. 69(7):2594-2602.

Despard, M.R., Perantie, D., Taylor, S., Grinstein-Weiss, M., Friedline, T. & Raghavan, R. 2016. Student debt and hardship: *Evidence from a large sample of low-and moderate-income households*. Children and Youth Services Review. 70:8-18.

Disney, R. & Gathergood, J. 2013. Financial literacy and consumer credit portfolios. *Journal of Banking & Finance*. 37(7):2246-2254.

Drentea, P. & Reynolds, J.R. 2012. Neither a borrower nor a lender be: The relative importance of debt and SES for mental health among older adults. *Journal of Aging and Health*. 24(4):673-695.

Drentea, P. & Reynolds, J.R. 2015. Where does debt fit in the stress process model? *Society and Mental Health*. 5(1):16-32.

Dwyer, R.E., McCloud, L. & Hodson, R. 2011. Youth debt, mastery, and self-esteem: Class-stratified effects of indebtedness on self-concept. *Social Science Research*. 40(3):727-741.

Easterlin, R.A. 2001. Income and happiness: Towards a unified theory. *The Economic Journal*. 111(473):465-484.

Eyal, K. 2016. Follow the Child: The Effect of an Unconditional Cash Transfer on Adolescent Human Capital and Mental Health.

Fitch, C., Chaplin, R., Trend, C. & Collard, S. 2007. Debt and mental health: the role of psychiatrists. *Advances in Psychiatric Treatment*. 13(3):194-202.

Frey, B.S. 2008. Happiness: A revolution in economics. MIT press. Available: .

Gathergood, J. 2012. Debt and depression: causal links and social norm effects. *The Economic Journal*. 122(563):1094-1114.

Gathergood, J. 2013. Personal debt and psychological health.

Gicheva, D. 2016. Student loans or marriage? A look at the highly educated. *Economics of Education Review*. 53:207-216.

Hamad, R., Fernald, L., Karlan, D. & Zinman, J. (2008), 'Social and economic correlates of depressive symptoms and perceived stress in South African adults', *Journal of Epidemiology and Community Health* 62(6), 538–544.

Headey, B. & Wooden, M. 2004. The effects of wealth and income on subjective well-being and ill-being. Economic Record. 80:S33.

Hojman, D.A., Miranda, Á & Ruiz-Tagle, J. 2016. Debt trajectories and mental health. Social Science & Medicine. 167:54-62.

Ifcher, J. & Zarghamee, H. 2011. Happiness and time preference: The effect of positive affect in a random-assignment experiment. American Economic Review. 101(7):3109-3129.

Kahn, M.E. 2015. A review of the age of sustainable development by Jeffrey Sachs. Journal of Economic Literature. 53(3):654-666.

Keese, M. & Schmitz, H. 2014. Broke, ill, and obese: is there an effect of household debt on health? Review of Income and Wealth. 60(3):525-541.

Kilburn, K., Thirumurthy, H., Halpern, C. T., Pettifor, A. & Handa, S. (2015), 'Effects of a Large-Scale Unconditional Cash Transfer Program on Mental Health Outcomes of Young People in Kenya', *Journal of Adolescent Health*.

Khumalo, K. Financial stress is making us sick. *Personal Finance* URL: https://www.iol.co.za/personal-finance/financial-stress-is-making-us-sick-11670666

Livingstone, S.M. & Lunt, P.K. 1992. Predicting personal debt and debt repayment: Psychological, social and economic determinants.

Lund, C. (2012), 'Poverty and mental health: a review of practice and policies', *Neuropsychiatry* 2(3), 213–219.

Lund, C., Breen, A., Flisher, A. J., Kakuma, R., Corrigall, J., Joska, J. A., Swartz, L. & Patel, V. (2010), 'Poverty and common mental disorders in low and middle income countries: a systematic review', *Social Science & Medicine* 71(3), 517 – 528.

Lund, C., Kleintjes, S., Kakuma, R. & Flisher, A. J. (2010), 'Public sector mental health systems in South Africa: inter-provincial comparisons and policy implications', *Social Psychiatry and Psychiatric Epidemiology* 45(3), 393–404.

Mani, A., Mullainathan, S., Shafir, E. & Zhao, J. 2013. Poverty impedes cognitive function. Science. 341(6149):976-980.

Mungai, K. & Bayat, A. 2018. High-functioning depression among women in South Africa: An exploratory study. Journal of Psychology in Africa. 28(5):411-415.

National Credit Regulator. 2018. Annual Report 2017/2018. [URL: https://www.thedti.gov.za/parliament/2018/NCR_AR_2018.pdf]

Pretorius, T. B. (1991), 'Cross-cultural application of the Center for Epidemiological Studies Depression Scale: a study of black South African students', *Psychological Reports* 69(3f), 1179–1185.

Radloff, L.S. 1977. The CES-D scale: A self-report depression scale for research in the general population. Applied Psychological Measurement. 1(3):385-401.

Reading, R. & Reynolds, S. 2001. Debt, social disadvantage and maternal depression. Social Science & Medicine. 53(4):441-453.

Richardson, T., Elliott, P. & Roberts, R. 2013. The relationship between personal unsecured debt and mental and physical health: a systematic review and meta-analysis. Clinical Psychology Review. 33(8):1148-1162.

Sachs, J.D. 2015. The age of sustainable development. Columbia University Press. Available: .

Sachs, J.D. 2016. Happiness and sustainable development: Concepts and evidence. World Happiness. :56.

Selenko, E. & Batinic, B. 2011. Beyond debt. A moderator analysis of the relationship between perceived financial strain and mental health. Social Science & Medicine. 73(12):1725-1732.

Shen, S., Sam, A.G. & Jones, E. 2014. Credit Card Indebtedness and Psychological Well-Being Over Time: Empirical Evidence from a Household Survey. Journal of Consumer Affairs. 48(3):431-456.

Silva, J.S. & Kemp, G.C. 2016. Partial effects in fixed effects models. United Kingdom Stata Users' Group Meetings. Available: .

Simmons, J. 2013. The relationship between consumer debt and mental health.

Sweet, E. 2011. Symbolic capital, consumption, and health inequality. American Journal of Public Health. 101(2):260-264.

Sweet, E., Kuzawa, C.W. & McDade, T.W. 2018. Short-term Lending: Payday Loans as Risk Factors for Anxiety, Inflammation and Poor Health. SSM-Population Health.

Sweet, E., Nandi, A., Adam, E.K. & McDade, T.W. 2013. The high price of debt: Household financial debt and its impact on mental and physical health. Social Science & Medicine. 91:94-100.

South African Depression and Anxiety Group. 2017. Depression.- the silent killer. URL: http://www.sadag.org/images/brochures/Depression-Infographics-2017.pdf

Southern Africa Labour and Development Research Unit. 2018. National Income Dynamics Study 2017, Waves 1 to 5 [datasets]. Version 1.0.0 Pretoria: Department of Planning, Monitoring, and Evaluation [funding agency]. Cape Town: Southern Africa Labour and Development Research Unit [implementer], 2018. Cape Town: DataFirst [distributor], 2018. https://doi.org/10.25828/fw3h-v708

Tay, L., Batz, C., Parrigon, S. & Kuykendall, L. 2017. Debt and subjective well-being: The other side of the income-happiness coin. Journal of Happiness Studies. 18(3):903-937.

Tella, R.D., MacCulloch, R.J. & Oswald, A.J. 2003. The macroeconomics of happiness. Review of Economics and Statistics. 85(4):809-827.

Walsemann, K.M., Gee, G.C. & Gentile, D. 2015. Sick of our loans: Student borrowing and the mental health of young adults in the United States. Social Science & Medicine. 124:85-93.

Ward, S.J. & King, L.A. 2016. Poor but happy? Income, happiness, and experienced and expected meaning in life. Social Psychological and Personality Science. 7(5):463-470.

World Bank 'Global Findex 2017' available at *https://globalfindex.worldbank.org/*, accessed 28 September 2018.

World Bank Group ‘`Financial Inclusion’ available at *https://www.worldbank.org/en/topic/financialinclusion/overview,* accessed 28 August 2018

World Bank Group ‘Republic of South Africa Systematic Country Diagnostic: An Incomplete Transition Overcoming the Legacy of Exclusion in South Africa’ (2018) at 18-19 available at *http://documents.worldbank.org/curated/en/815401525706928690/pdf/WBG-South-Africa-Systematic-Country-Diagnostic-FINAL-for-board-SECPO-Edit-05032018.pdf,* accessed28 September 2018.

Wooldridge, J.M. 2015. Introductory econometrics: A modern approach. Nelson Education. Available: .

Yunus, M. 2007. Credit for the poor: Poverty as distant history. Harvard International Review. 29(3):20.

**DATA**

**Wave 5:** Southern Africa Labour and Development Research Unit. National Income Dynamics Study 2017, Wave 5 [dataset]. Version 1.0.0 Pretoria: Department of Planning, Monitoring, and Evaluation [funding agency]. Cape Town: Southern Africa Labour and Development Research Unit [implementer], 2018. Cape Town: DataFirst [distributor], 2018. https://doi.org/10.25828/fw3h-v708

**Wave 4:** Southern Africa Labour and Development Research Unit. National Income Dynamics Study 2014-2015, Wave 4 [dataset]. Version 2.0.0. Pretoria: Department of Planning, Monitoring, and Evaluation [funding agency]. Cape Town: Southern Africa Labour and Development Research Unit, 2018. Cape Town: DataFirst [distributor], 2018. https://doi.org/10.25828/f4ws-8a78

**Wave 3:** Southern Africa Labour and Development Research Unit. National Income Dynamics Study Wave 3, 2012 [dataset]. Version 3.0.0. Pretoria: SA Presidency [funding agency]. Cape Town: Southern Africa Labour and Development Research Unit, 2018. Cape Town: DataFirst [distributor], 2018. https://doi.org/10.25828/7pgq-q106

**Wave 2:** Southern Africa Labour and Development Research Unit. National Income Dynamics Study Wave 2, 2010-2011 [dataset]. Version 4.0.0. Pretoria: SA Presidency [funding agency]. Cape Town: Southern Africa Labour and Development Research Unit, 2018. Cape Town: DataFirst [distributor], 2018. https://doi.org/10.25828/j1h1-5m16

**Wave 1:** Southern Africa Labour and Development Research Unit. National Income Dynamics Study (NIDS) Wave 1, 2008 [dataset]. Version 7.0.0. Pretoria: SA Presidency [funding agency]. Cape Town: Southern Africa Labour and Development Research Unit, 2018. Cape Town: DataFirst [distributor], 2018. https://doi.org/10.25828/e7w9-m033

## Appendix

### A1: Cross tabulation comparing percentage of employed and unemployed individuals with debt

| | **Has debt** | **No debt** |
|---|---|---|
| **Employed** | 19.72 | 26.49 |
| **Unemployed** | 7.24 | 46.54 |

Source: NIDS(2008-2017) own calculation
Notes: Balanced panel over 5 waves, inclusive of employed individuals

### A2: Full regression from Table 12 – Logistic fixed effects regressions for the effect of debt on depression

Dependent variable: **Depressed$_{(t)}$ = 1**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Depressed $_{(t-1)}$ = 1 | | 0.168*** | 0.247*** | 0.247*** |
| | | (0.0175) | (0.0307) | (0.0307) |

| | | | | |
|---|---|---|---|---|
| Any debt $_{(t-1)}$ = 1 | 1.059 | 1.047 | 1.310** | 1.315** |
| | (0.0909) | (0.0964) | (0.139) | (0.146) |
| Depressed $_{(t-1)}$ x Any debt $_{(t-1)}$ =1 | | | 0.342*** | 0.342*** |
| | | | (0.0758) | (0.0759) |
| Any debt $_{(t)}$ = 1 | | | | 1.011 |
| | | | | (0.102) |
| Age | 0.981 | 1.068 | 1.056 | 1.056 |
| | (0.0534) | (0.0762) | (0.0751) | (0.0754) |
| Age squared | 1.001 | 1.000 | 1.000 | 1.000 |
| | (0.000651) | (0.000844) | (0.000842) | (0.000844) |
| Primary School = 1 | 2.803 | 4.200 | 3.625 | 3.629 |
| | (2.179) | (4.782) | (3.732) | (3.735) |
| High School (no matric) = 1 | 1.721 | 2.441 | 2.156 | 2.158 |
| | (1.369) | (2.866) | (2.289) | (2.291) |
| Matric = 1 | 3.391 | 4.793 | 4.383 | 4.384 |
| | (2.894) | (5.912) | (4.951) | (4.952) |
| Further Education = 1 | 1.633 | 2.160 | 1.814 | 1.815 |
| | (1.348) | (2.586) | (1.978) | (1.978) |
| Higher Education = 1 | 3.191 | 4.508 | 4.309 | 4.318 |
| | (2.944) | (5.882) | (5.249) | (5.261) |
| Living together/married =1 | 0.732** | 0.690** | 0.662*** | 0.662*** |
| | (0.0985) | (0.105) | (0.102) | (0.102) |
| Bad physical health = 1 | 1.624 | 1.317 | 1.269 | 1.268 |
| | (0.511) | (0.518) | (0.516) | (0.515) |
| Ln of income | 0.831*** | 0.839** | 0.830** | 0.830** |
| | (0.0571) | (0.0683) | (0.0688) | (0.0688) |
| Urban = 1 | 1.329 | 1.590* | 1.590* | 1.590* |
| | (0.281) | (0.424) | (0.416) | (0.416) |
| Observations | 3,503 | 3,432 | 3,432 | 3,430 |

Source: Estimation based on data from NIDS (2008-2017), own calculations
Notes: Dependent variable: Depression$_{(t)}$ (CES-D 10 Score>10) =1
Four separate regressions each in their own column from 1 to 4. All regressions are logistic fixed effects

(1) Any debt in previous time period
(2) (1) and previous time period depression status
(3) (2) and an interaction term for previous depression and debt in the previous period
(4) (3) and current period debt status

Additional controls: age, age squared, education, income, marital status, household size, physical health status, geographical location type (urban vs traditional/rural) Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**A3: Full regression from Table 13. Logistic regression estimates presenting the effect of independently run regression reporting the effect of all debt types on depression**

| Dependent variable: **Depressed$_{(t)}$ = 1** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (3) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| Formal debt $_{(t)}$ = 1 | 0.876*** | 0.890** | 0.932 | 1.014 | 0.972 | 0.892 | 1.047 | 1.062 | 0.878 |
| | (0.0402) | (0.0505) | (0.0622) | (0.0918) | (0.130) | (0.140) | (0.0994) | (0.110) | (0.165) |
| Informal debt $_{(t)}$ = 1 | 1.360*** | 1.501*** | 1.160 | 1.482** | 1.844*** | 2.702*** | 1.183 | 1.386* | 2.324*** |
| | (0.107) | (0.138) | (0.131) | (0.232) | (0.395) | (0.757) | (0.185) | (0.245) | (0.661) |
| Student debt $_{(t)}$ = 1 | 0.937 | 1.117 | 1.335 | 2.257 | 1.046 | 1.288 | 2.245 | 2.470* | 2.571 |
| | (0.203) | (0.306) | (0.412) | (1.162) | (0.717) | (1.001) | (1.139) | (1.259) | (3.021) |
| Secure debt $_{(t)}$ = 1 | 1.006 | 0.852 | 0.791 | 0.841 | 1.275 | 1.326 | 0.701 | 0.651 | 0.939 |
| | (0.105) | (0.141) | (0.131) | (0.217) | (0.496) | (0.575) | (0.193) | (0.190) | (0.454) |
| Formal debt $_{(t-1)}$ = 1 | | 0.982 | | 1.020 | | 0.998 | | 1.058 | 1.011 |
| | | (0.0591) | | (0.0933) | | (0.155) | | (0.109) | (0.179) |
| Informal debt $_{(t-1)}$ = 1 | | 1.219* | | 1.507** | | 1.818* | | 1.688*** | 1.945* |
| | | (0.134) | | (0.261) | | (0.611) | | (0.335) | (0.736) |
| Student debt $_{(t-1)}$ = 1 | | 0.681 | | 0.953 | | 1.174 | | 1.463 | 1.637 |
| | | (0.205) | | (0.410) | | (1.005) | | (0.702) | (1.532) |
| Secure debt $_{(t-1)}$ = 1 | | 1.173 | | 0.922 | | 0.760 | | 0.674 | 0.577 |
| | | (0.187) | | (0.221) | | (0.317) | | (0.178) | (0.249) |
| Age | 1.011 | 1.027 | 1.000 | 0.980 | 0.991 | 0.982 | 1.070 | 1.070 | 1.120 |
| | (0.0143) | (0.0185) | (0.0354) | (0.0552) | (0.0839) | (0.100) | (0.0772) | (0.0790) | (0.146) |
| Age squared | 1.000 | 1.000 | 1.000 | 1.001 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | (0.000174) | (0.000220) | (0.000430) | (0.000674) | (0.00101) | (0.00121) | (0.000859) | (0.000872) | (0.00151) |
| Primary School = 1 | 0.985 | 0.991 | 1.512 | 2.809 | 1.184 | 3.348 | 4.075 | 4.176 | 5.958 |
| | (0.0964) | (0.124) | (0.591) | (2.147) | (1.562) | (4.814) | (4.499) | (4.558) | (13.33) |
| High School(no matric) = 1 | 0.880 | 0.889 | 1.113 | 1.642 | 0.935 | 2.039 | 2.332 | 2.346 | 5.510 |
| | (0.0857) | (0.111) | (0.471) | (1.289) | (1.333) | (3.191) | (2.671) | (2.679) | (12.77) |
| Matric = 1 | 0.840* | 0.831 | 1.802 | 3.102 | 1.136 | 1.985 | 4.345 | 4.255 | 4.084 |
| | (0.0874) | (0.110) | (0.841) | (2.621) | (1.670) | (3.197) | (5.250) | (5.125) | (9.687) |
| Further Education = 1 | 0.859 | 0.854 | 1.188 | 1.557 | 0.532 | 1.019 | 1.992 | 2.070 | 2.870 |
| | (0.112) | (0.136) | (0.536) | (1.271) | (0.771) | (1.619) | (2.327) | (2.410) | (6.732) |
| Higher Education = 1 | 0.763* | 0.711* | 1.279 | 2.866 | 0.843 | 1.579 | 4.267 | 4.334 | 4.971 |
| | (0.113) | (0.134) | (0.713) | (2.659) | (1.316) | (2.682) | (5.482) | (5.606) | (12.17) |
| Female = 1 | 1.154*** | 1.165*** | | | | | | | |
| | (0.0502) | (0.0629) | | | | | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Living together/married = 1 | 0.778*** | 0.723*** | 0.809** | 0.753** | 0.751 | 0.668* | 0.709** | 0.726** | 0.720 |
| | (0.0359) | (0.0415) | (0.0792) | (0.104) | (0.147) | (0.151) | (0.109) | (0.112) | (0.194) |
| Bad physical health = 1 | 2.355*** | 1.741*** | 1.765** | 1.594 | 1.271 | 1.098 | 1.257 | 1.299 | 1.012 |
| | (0.317) | (0.330) | (0.400) | (0.511) | (0.604) | (0.625) | (0.499) | (0.509) | (0.749) |
| Ln total individual income = 1 | 0.839*** | 0.856*** | 0.850*** | 0.819*** | 0.876 | 0.852 | 0.824** | 0.827** | 0.771 |
| | (0.0228) | (0.0282) | (0.0430) | (0.0578) | (0.110) | (0.130) | (0.0696) | (0.0705) | (0.157) |
| African = 1 | 1.774*** | 1.662*** | | | | | | | |
| | (0.226) | (0.317) | | | | | | | |
| Coloured = 1 | 1.047 | 0.971 | | | | | | | |
| | (0.141) | (0.194) | | | | | | | |
| Asian = 1 | 1.728** | 1.596 | | | | | | | |
| | (0.377) | (0.503) | | | | | | | |
| Urban=1 | 1.117** | 1.178*** | 1.051 | 1.432* | 0.725 | 0.748 | 1.597* | 1.654* | 1.170 |
| | (0.0506) | (0.0654) | (0.160) | (0.311) | (0.272) | (0.316) | (0.438) | (0.451) | (0.661) |
| Negative net worth = 1 | | | | | 1.821** | 1.745* | | | 2.225*** |
| | | | | | (0.481) | (0.525) | | | (0.667) |
| Depressed $_{(t-1)}$ = 1 | | | | | | | 0.164*** | 0.159*** | 0.152*** |
| | | | | | | | (0.0177) | (0.0176) | (0.0325) |
| Constant | 0.401** | 0.250*** | | | | | | | |
| | (0.144) | (0.118) | | | | | | | |
| Observations | 18,182 | 12,207 | 6,254 | 3,416 | 1,422 | 1,147 | 3,382 | 3,345 | 1,130 |
| Number of pid | 8,216 | 6,333 | | | | | | | |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| FE | | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged debt | | ✓ | | ✓ | | ✓ | | ✓ | ✓ |
| Negative net worth | | | | | ✓ | ✓ | | | ✓ |
| Lagged depression | | | | | | | ✓ | ✓ | ✓ |

Source: Estimation based on data from NIDS (2008-2017), own calculations
Notes: Dependent variable: Depression$_{(t)}$ (CES-D 10 Score>10) =1
Four separate regressions each in their own column from 1 to 4. All regressions are logistic fixed effects
Additional controls: age, age squared, education, income, marital status, household size, physical health status, geographical location type (urban vs traditional/rural) Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

## A4: Full regression for Table 14. Logistic regression estimates presenting the effect of independently run regression reporting the effect of each type of debt on depression

Dependent variable: **Depressed$_{(t)}$ = 1**

| | All debt | | Formal debt | | Informal debt | | Student debt | | Secure debt | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Depressed$_{(t-1)}$ = 1 | 0.247*** | 0.247*** | 0.228*** | 0.227*** | 0.174*** | 0.174*** | 0.167*** | 0.168*** | 0.169*** | 0.165*** |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (0.0307) | (0.0307) | (0.0270) | (0.0271) | (0.0190) | (0.0190) | (0.0176) | (0.0177) | (0.0181) | (0.0179) |
| Any debt $_{(t-1)}$ = 1 | 1.310** | 1.315** | | | | | | | | |
| | (0.139) | (0.146) | | | | | | | | |
| Depressed $_{(t-1)}$ x Any debt $_{(t-1)}$ =1 | 0.342*** | 0.342*** | | | | | | | | |
| | (0.0758) | (0.0759) | | | | | | | | |
| Any debt $_{(t)}$ = 1 | | 1.011 | | | | | | | | |
| | | (0.102) | | | | | | | | |
| Age | 1.056 | 1.056 | 1.071 | 1.076 | 1.070 | 1.055 | 1.080 | 1.075 | 1.080 | 1.085 |
| | (0.0751) | (0.0754) | (0.0765) | (0.0772) | (0.0764) | (0.0756) | (0.0769) | (0.0767) | (0.0773) | (0.0782) |
| Age squared | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | (0.000842) | (0.000844) | (0.000845) | (0.000848) | (0.000848) | (0.000851) | (0.000845) | (0.000849) | (0.000850) | (0.000855) |
| Primary School = 1 | 3.625 | 3.629 | 3.735 | 3.783 | 4.466 | 4.356 | 4.228 | 4.237 | 4.210 | 4.054 |
| | (3.732) | (3.735) | (3.913) | (3.952) | (4.977) | (4.891) | (4.807) | (4.829) | (4.765) | (4.370) |
| High School(no matric) = 1 | 2.156 | 2.158 | 2.193 | 2.219 | 2.497 | 2.399 | 2.466 | 2.479 | 2.456 | 2.347 |
| | (2.289) | (2.291) | (2.368) | (2.393) | (2.885) | (2.794) | (2.894) | (2.915) | (2.869) | (2.631) |
| Matric = 1 | 4.383 | 4.384 | 4.504 | 4.539 | 4.743 | 4.596 | 4.944 | 4.719 | 4.838 | 4.581 |
| | (4.951) | (4.952) | (5.174) | (5.205) | (5.761) | (5.622) | (6.097) | (5.839) | (5.937) | (5.422) |
| Further Education = 1 | 1.814 | 1.815 | 1.921 | 1.922 | 2.200 | 2.152 | 2.230 | 2.192 | 2.162 | 2.048 |
| | (1.978) | (1.978) | (2.128) | (2.125) | (2.592) | (2.554) | (2.668) | (2.628) | (2.574) | (2.344) |
| Higher Education = 1 | 4.309 | 4.318 | 4.293 | 4.769 | 4.377 | 4.331 | 4.870 | 4.604 | 4.511 | 4.254 |
| | (5.249) | (5.261) | (5.306) | (5.902) | (5.684) | (5.669) | (6.372) | (6.015) | (5.859) | (5.361) |
| Female = 1 | 0.662*** | 0.662*** | 0.668*** | 0.678** | 0.690** | 0.692** | 0.685** | 0.690** | 0.690** | 0.698** |
| | (0.102) | (0.102) | (0.102) | (0.104) | (0.106) | (0.106) | (0.104) | (0.105) | (0.105) | (0.107) |
| Living together/married = 1 | 1.269 | 1.268 | 1.297 | 1.293 | 1.306 | 1.262 | 1.335 | 1.314 | 1.328 | 1.323 |
| | (0.516) | (0.515) | (0.512) | (0.509) | (0.521) | (0.501) | (0.529) | (0.521) | (0.524) | (0.524) |
| Bad physical health = 1 | 0.830** | 0.830** | 0.829** | 0.816** | 0.840** | 0.849** | 0.836** | 0.827** | 0.837** | 0.838** |
| | (0.0688) | (0.0688) | (0.0694) | (0.0695) | (0.0683) | (0.0686) | (0.0688) | (0.0689) | (0.0686) | (0.0692) |
| Ln total individual income = 1 | 1.590* | 1.590* | 1.593* | 1.583* | 1.626* | 1.634* | 1.609* | 1.634* | 1.596* | 1.589* |
| | (0.416) | (0.416) | (0.421) | (0.418) | (0.433) | (0.437) | (0.428) | (0.434) | (0.425) | (0.433) |
| Formal debt $_{(t-1)}$ = 1 | | | 1.252** | 1.282** | | | | | | |
| | | | (0.135) | (0.146) | | | | | | |
| Depressed $_{(t-1)}$ x Formal debt $_{(t-1)}$ =1 | | | 0.365*** | 0.363*** | | | | | | |
| | | | (0.0809) | (0.0808) | | | | | | |
| Formal debt $_{(t)}$ = 1 | | | | 1.059 | | | | | | |
| | | | | (0.108) | | | | | | |
| Informal debt $_{(t-1)}$ = 1 | | | | | 1.722** | 1.970*** | | | | |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | (0.388) | (0.488) | | | | |
| Depressed $_{(t-1)}$ x Informal debt $_{(t-1)}$ =1 | | | | | 0.538* | 0.540* | | | | |
| | | | | | (0.198) | (0.194) | | | | |
| Informal debt $_{(t)}$ = 1 | | | | | | 1.390* | | | | |
| | | | | | | (0.248) | | | | |
| Student debt $_{(t-1)}$ = 1 | | | | | | | 1.406 | 1.738 | | |
| | | | | | | | (0.760) | (1.125) | | |
| Depressed $_{(t-1)}$ x Student debt $_{(t-1)}$ =1 | | | | | | | 0.444 | 0.562 | | |
| | | | | | | | (0.336) | (0.463) | | |
| Student debt $_{(t)}$ = 1 | | | | | | | | 2.444* | | |
| | | | | | | | | (1.255) | | |
| Secure debt $_{(t-1)}$ = 1 | | | | | | | | | 0.770 | 0.722 |
| | | | | | | | | | (0.204) | (0.201) |
| Depressed $_{(t-1)}$ x Secure debt $_{(t-1)}$ =1 | | | | | | | | | 0.722 | 0.670 |
| | | | | | | | | | (0.334) | (0.318) |
| Secure debt $_{(t)}$ = 1 | | | | | | | | | | 0.649 |
| | | | | | | | | | | (0.192) |
| Observations | 3,432 | 3,430 | 3,422 | 3,404 | 3,405 | 3,396 | 3,421 | 3,404 | 3,427 | 3,422 |

Source: Estimation based on data from NIDS (2008-2017), own calculations
Notes: Dependent variable: Depression$_{(t)}$ (CES-D 10 Score>10) =1
Four separate regressions each in their own column from 1 to 4. All regressions are logistic fixed effects
Additional controls: age, age squared, education, income, marital status, household size, physical health status, geographical location type (urban vs traditional/rural) Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

## A5: Full regression for Table 15. Standard logistic and fixed effects logistic estimates for including all debt categories

| Dependent variable: **Depressed$_{(t)}$ = 1** | | | | |
|---|---|---|---|---|
| | Logit | Fixed effects | Logit | Fixed Effects |
| | (1) | (2) | (3) | (4) |
| Depressed$_{(t-1)}$ = 1 | 1.001 | 0.229*** | 0.964 | 0.271*** |
| | (0.0827) | (0.0293) | (0.108) | (0.0658) |
| Formal debt $_{(t)}$ = 1 | 0.882** | 1.042 | 0.879* | 0.869 |
| | (0.0503) | (0.109) | (0.0680) | (0.168) |
| Informal debt $_{(t)}$ = 1 | 1.495*** | 1.398* | 1.595*** | 2.268*** |

| | | | | |
|---|---|---|---|---|
| | (0.138) | (0.252) | (0.183) | (0.674) |
| Student debt $_{(t)}$ = 1 | 1.154 | 2.362 | 0.860 | 2.378 |
| | (0.316) | (1.259) | (0.310) | (2.605) |
| Secure debt $_{(t)}$ = 1 | 0.857 | 0.649 | 0.935 | 0.922 |
| | (0.142) | (0.197) | (0.202) | (0.462) |
| Formal debt $_{(t)}$ = 1 | 0.998 | 1.288** | 0.960 | 1.399 |
| | (0.0652) | (0.150) | (0.0828) | (0.287) |
| Informal debt $_{(t-1)}$ = 1 | 1.179 | 2.038*** | 1.200 | 2.975** |
| | (0.149) | (0.501) | (0.197) | (1.479) |
| Student debt $_{(t-1)}$ = 1 | 0.551* | 1.604 | 0.509 | 1.080 |
| | (0.196) | (1.024) | (0.246) | (1.384) |
| Secure debt $_{(t-1)}$ = 1 | 1.219 | 0.643 | 0.947 | 0.458* |
| | (0.202) | (0.181) | (0.211) | (0.210) |
| Depressed $_{(t-1)}$ x Formal debt $_{(t-1)}$ =1 | 0.958 | 0.370*** | 0.879 | 0.212*** |
| | (0.142) | (0.0856) | (0.177) | (0.0913) |
| Depressed $_{(t-1)}$ x Informal debt $_{(t-1)}$ =1 | 1.085 | 0.519* | 0.707 | 0.351 |
| | (0.289) | (0.204) | (0.289) | (0.226) |
| Depressed $_{(t-1)}$ x Student debt $_{(t-1)}$ =1 | 2.759 | 1.188 | 3.799 | 5.228 |
| | (1.864) | (0.978) | (3.817) | (7.693) |
| Depressed $_{(t-1)}$ x Secure debt $_{(t-1)}$ =1 | 0.760 | 0.890 | 1.310 | 2.803 |
| | (0.315) | (0.433) | (0.632) | (2.194) |
| Age | 1.023 | 1.064 | 1.024 | 1.100 |
| | (0.0185) | (0.0785) | (0.0264) | (0.144) |
| Age squared | 1.000 | 1.000 | 1.000 | 1.000 |
| | (0.000220) | (0.000873) | (0.000312) | (0.00152) |
| Primary School = 1 | 1.008 | 3.776 | 1.005 | 4.506 |
| | (0.127) | (3.744) | (0.188) | (8.450) |
| High School(no matric) = 1 | 0.899 | 2.135 | 0.902 | 3.636 |
| | (0.113) | (2.216) | (0.166) | (7.164) |
| Matric = 1 | 0.836 | 4.033 | 0.837 | 2.676 |
| | (0.111) | (4.479) | (0.161) | (5.458) |
| Further Education = 1 | 0.867 | 1.815 | 0.817 | 1.725 |
| | (0.139) | (1.934) | (0.182) | (3.465) |
| Higher Education = 1 | 0.700* | 4.355 | 0.705 | 3.311 |
| | (0.134) | (5.313) | (0.183) | (7.052) |
| Female = 1 | 1.164*** | | 1.137* | |
| | (0.0632) | | (0.0842) | |
| Living together/married = 1 | 0.723*** | 0.697** | 0.714*** | 0.721 |
| | (0.0419) | (0.109) | (0.0560) | (0.201) |
| Bad physical health = 1 | 1.591** | 1.231 | 1.275 | 0.879 |
| | (0.312) | (0.497) | (0.360) | (0.737) |
| Ln total individual income = 1 | 0.862*** | 0.813** | 0.862*** | 0.757 |
| | (0.0286) | (0.0709) | (0.0379) | (0.159) |
| African = 1 | 1.680*** | | 1.506* | |
| | (0.321) | | (0.339) | |
| Coloured = 1 | 0.986 | | 0.691 | |
| | (0.197) | | (0.167) | |
| Asian = 1 | 1.628 | | 0.899 | |
| | (0.513) | | (0.395) | |
| Urban=1 | 1.169*** | 1.668* | 1.472*** | 1.146 |
| | (0.0653) | (0.446) | (0.116) | (0.605) |
| Negative net worth = 1 | | | 1.197 | 2.597*** |

| | | | | |
|---|---|---|---|---|
| | | | (0.179) | (0.864) |
| Constant | 0.251*** | | 0.226** | |
| | (0.120) | | (0.147) | |
| | | | | |
| Observations | 12,045 | 3,345 | 7,209 | 1,130 |
| Number of pid | 6,293 | | 4,944 | |

Source: Estimation based on data from NIDS (2008-2017), own calculations
Notes: Dependent variable: $Depression_{(t)}$ (CES-D 10 Score>10) =1
Four separate regressions each in their own column from 1 to 4. All regressions are logistic fixed effects
Additional controls: age, age squared, education, income, marital status, household size, physical health status, geographical location type (urban vs traditional/rural) Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

## A6: Full regression from Table 16 – Logistic fixed effects regressions for the effect of being depressed on having any debt

| Dependent variable: **Any debt $_{(t)}$ = 1** | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Depressed $_{(t-1)}$ = 1 | 1.033 | 0.952 | 0.838 | 0.818* |
| | (0.0853) | (0.0853) | (0.0929) | (0.0941) |
| Any debt $_{(t-1)}$ = 1 | | 0.220*** | 0.207*** | 0.207*** |
| | | (0.0170) | (0.0176) | (0.0177) |
| Depressed $_{(t-1)}$ x Any debt $_{(t-1)}$ =1 | | | 1.393* | 1.374* |
| | | | (0.264) | (0.265) |
| Depressed $_{(t)}$ = 1 | | | | 0.978 |
| | | | | (0.0964) |
| Age | 1.428*** | 1.797*** | 1.800*** | 1.766*** |
| | (0.0719) | (0.118) | (0.118) | (0.117) |
| Age squared | 0.997*** | 0.996*** | 0.995*** | 0.996*** |
| | (0.000609) | (0.000768) | (0.000768) | (0.000777) |
| Primary School = 1 | 1.891 | 2.233 | 2.290 | 2.233 |
| | (1.037) | (1.458) | (1.485) | (1.496) |
| High School (no matric) = 1 | 1.671 | 1.933 | 2.007 | 1.781 |
| | (0.987) | (1.404) | (1.453) | (1.344) |
| Matric = 1 | 2.199 | 2.479 | 2.573 | 2.337 |
| | (1.375) | (1.868) | (1.933) | (1.824) |
| Further Education = 1 | 2.311 | 2.730 | 2.847 | 2.678 |
| | (1.405) | (2.021) | (2.101) | (2.053) |
| Higher Education = 1 | 2.024 | 2.086 | 2.132 | 1.950 |
| | (1.437) | (1.748) | (1.783) | (1.682) |

| | | | | |
|---|---|---|---|---|
| Living together/married =1 | 0.987 | 0.947 | 0.948 | 0.964 |
| | (0.124) | (0.132) | (0.131) | (0.134) |
| Bad physical health = 1 | 2.211** | 2.006* | 1.984* | 2.174** |
| | (0.827) | (0.721) | (0.705) | (0.785) |
| Ln of income | 1.304*** | 1.337*** | 1.335*** | 1.352*** |
| | (0.0852) | (0.0941) | (0.0945) | (0.101) |
| Urban = 1 | 1.088 | 1.227 | 1.240 | 1.294 |
| | (0.212) | (0.261) | (0.264) | (0.284) |
| Observations | 4,948 | 4,948 | 4,948 | 4,869 |

Source: Estimation based on data from NIDS (2008-2017), own calculations
Notes: Dependent variable: Any debt =1
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

## <u>A7: Full regression from Table 17 – Logistic fixed effects regressions for the effect of being depressed on having debt for each category of debt</u>

Dependent variable(s): **Has debt category $_{(t)}$ = 1**

| | Any debt | | Formal debt | | Informal debt | | Secure debt | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Depressed $_{(t)}$ = 1 | | 0.978 | | 0.998 | | 1.428* | | 0.870 |
| | | (0.0964) | | (0.101) | | (0.261) | | (0.242) |
| Depressed $_{(t-1)}$ = 1 | 0.838 | 0.818* | 0.882 | 0.872 | 0.744* | 0.772 | 1.221 | 1.174 |
| | (0.0929) | (0.0941) | (0.101) | (0.104) | (0.132) | (0.151) | (0.423) | (0.441) |
| Any debt $_{(t-1)}$ = 1 | 0.207*** | 0.207*** | | | | | | |
| | (0.0176) | (0.0177) | | | | | | |
| Depressed $_{(t-1)}$ x Any debt $_{(t-1)}$ =1 | 1.393* | 1.374* | | | | | | |
| | (0.264) | (0.265) | | | | | | |
| Age | 1.800*** | 1.766*** | 1.825*** | 1.788*** | 1.441** | 1.371** | 2.085*** | 2.106*** |
| | (0.118) | (0.117) | (0.122) | (0.120) | (0.214) | (0.204) | (0.462) | (0.467) |
| Age squared | 0.995*** | 0.996*** | 0.995*** | 0.996*** | 0.998 | 0.999 | 0.992*** | 0.992*** |
| | (0.000768) | (0.000777) | (0.000786) | (0.000792) | (0.00177) | (0.00178) | (0.00242) | (0.00242) |
| Primary School | 2.290 | 2.233 | 4.169* | 4.042* | 0.485 | 0.464 | 8.63e-07*** | 1.00e-06*** |
| | (1.485) | (1.496) | (3.418) | (3.402) | (0.899) | (0.942) | (9.37e-07) | (1.16e-06) |
| High School(no matric) | 2.007 | 1.781 | 2.745 | 2.405 | 1.169 | 1.147 | 1.84e-07*** | 2.17e-07*** |
| | (1.453) | (1.344) | (2.407) | (2.186) | (2.312) | (2.473) | (2.80e-07) | (3.46e-07) |
| Matric | 2.573 | 2.337 | 3.911 | 3.445 | 0.966 | 0.965 | 4.71e-07*** | 5.30e-07*** |
| | (1.933) | (1.824) | (3.527) | (3.215) | (1.972) | (2.142) | (7.43e-07) | (8.73e-07) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Further Education | 2.847 | 2.678 | 4.061 | 3.674 | 1.272 | 1.423 | 4.25e-07*** | 5.12e-07*** |
| | (2.101) | (2.053) | (3.616) | (3.383) | (2.537) | (3.092) | (6.76e-07) | (8.46e-07) |
| Higher education = 1 | 2.132 | 1.950 | 2.867 | 2.658 | 0.107 | 0.104 | 1.02e-06*** | 1.18e-06*** |
| | (1.783) | (1.682) | (2.724) | (2.607) | (0.234) | (0.248) | (1.67e-06) | (2.02e-06) |
| Living together/married = 1 | 0.948 | 0.964 | 0.921 | 0.927 | 0.955 | 1.046 | 3.542*** | 3.474*** |
| | (0.131) | (0.134) | (0.128) | (0.131) | (0.262) | (0.291) | (1.559) | (1.535) |
| Bad physical health = 1 | 1.984* | 2.174** | 2.427** | 2.698*** | 2.782* | 2.620* | 0.893 | 0.908 |
| | (0.705) | (0.785) | (0.907) | (1.022) | (1.582) | (1.522) | (0.897) | (0.925) |
| Ln of income = 2 | 1.335*** | 1.352*** | 1.338*** | 1.359*** | 0.912 | 0.952 | 0.989 | 0.958 |
| | (0.0945) | (0.101) | (0.0989) | (0.106) | (0.126) | (0.130) | (0.131) | (0.149) |
| Urban = 1 | 1.240 | 1.294 | 1.234 | 1.299 | 1.009 | 0.955 | 1.300 | 1.277 |
| | (0.264) | (0.284) | (0.272) | (0.295) | (0.459) | (0.429) | (0.937) | (0.947) |
| Formal debt $_{(t)}$ = 1 | | | | | | | | |
| Formal debt $_{(t-1)}$ = 1 | | | 0.220*** | 0.221*** | | | | |
| | | | (0.0190) | (0.0191) | | | | |
| Depressed $_{(t-1)}$ x Formal debt $_{(t-1)}$ =1 | | | 1.295 | 1.287 | | | | |
| | | | (0.248) | (0.249) | | | | |
| Informal debt $_{(t)}$ = 1 | | | | | | | | |
| Informal debt $_{(t-1)}$ = 1 | | | | | 0.0694*** | 0.0633*** | | |
| | | | | | (0.0179) | (0.0170) | | |
| Depressed $_{(t-1)}$ x Informal debt $_{(t-1)}$ =1 | | | | | 1.471 | 1.442 | | |
| | | | | | (0.775) | (0.787) | | |
| Secure debt $_{(t)}$ = 1 | | | | | | | | |
| Secure debt $_{(t-1)}$ = 1 | | | | | | | 0.376*** | 0.379*** |
| | | | | | | | (0.0731) | (0.0741) |
| Depressed $_{(t-1)}$ x Secure debt $_{(t-1)}$ =1 | | | | | | | 0.650 | 0.646 |
| | | | | | | | (0.371) | (0.370) |
| Observations | 4,948 | 4,869 | 4,724 | 4,645 | 1,408 | 1,386 | 660 | 655 |
| Current debt included? | No | Yes | No | Yes | No | Yes | No | Yes |

Source: Estimation based on data from NIDS (2008-2017), own calculations
Notes: Dependent variables as follows:
(1-2): Any debt = 1
(3-4): Formal debt =1
(5-6) Informal debt =1
(7-8) Secure debt =1
Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1